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FINANCING THE GREEN TRANSITION IN THE MEDITERRANEAN: ASSESSING THE IMPACT AND DIVERSITY OF GREEN FINANCE TOOLS

Akdeniz'de Yeřil Dönüřümün Finansmanı: Yeřil Finansman Araçlarının Etki ve Çeřitliliğinin Değ erlendirilmesi

Sevil ACAR*^{ID} & Constantin TSAKAS**^{ID}

Abstract

This study examines the effects of environmentally related taxes and feed-in tariffs (FiTs) on greenhouse gas (GHG) emissions in Mediterranean countries, while also exploring the role of broader green finance instruments in the region. The study highlights several key findings. First, environmentally related taxes and climate taxes, while not significantly reducing per capita GHG emissions when applied alone, appear to become more effective when combined with stringent environmental policies. Specifically, a 1 percentage point increase in these taxes leads to a 0.01-0.02% decrease in GHG emissions per capita, with more stringent policies amplifying their impact. Similarly, the presence of FiTs does not consistently reduce emissions unless tariffs are increased for specific energy sources such as hydro, waste, or marine energy, leading to a more pronounced decline in emissions. Green finance mechanisms are necessary but not sufficient on their own; their success depends on alignment with complementary fiscal and regulatory policies. A comprehensive policy mix—phasing out fossil fuel subsidies, implementing carbon pricing, and reinforcing environmental regulation—is crucial for enabling a credible transition to a low-carbon economy in the Mediterranean.

Öz

Bu çalışma, çevresel nitelikli vergilerin ve yenilenebilir enerji alım garantilerinin (Feed-in Tariff, FiT) Akdeniz ülkelerinde sera gazı (GHG) emisyonları üzerindeki etkilerini incelemekte ve aynı zamanda bölgedeki daha geniş kapsamlı yeřil finansman araçlarının rolünü değerlendirmektedir. Çalışma, birkaç temel bulgu ortaya koymaktadır. İlk olarak, çevresel nitelikli vergiler ve iklim vergileri tek başlarına uygulandıklarında kişi başına düş en sera gazı emisyonlarını anlamlı ölçüde azaltmasa da sıkı çevre politikaları ile birlikte uygulandıklarında daha etkili hale gelmektedir. Nitekim bu vergilerdeki 1 yüzde puanlık artışın, kişi başına düş en sera gazı emisyonlarında %0,01–0,02 oranında bir azalma ile ilişkili oldu ğ u ve daha sıkı düzenlemelerin bu etkiyi güç lendirdiğ i tespit edilmektedir. Benzer şekilde, alım garantilerinin (FiT'lerin) varlığı, hidroelektrik, atık ya da deniz enerjisi gibi belirli enerji kaynaklarına yönelik FiT fiyatları artırılmadıkça emisyonları tutarlı biçimde azaltmamaktadır; ancak bu kaynaklara yönelik tarife artışları emisyonlarda daha belirgin bir düş üř sağlamaktadır. Bulgular, yeřil finansman mekanizmalarının gerekli olmakla birlikte tek başına yeterli olmadığ ını göstermektedir; bu araçların başarısı, tamamlayıcı mali ve düzenleyici politikalarla uyum içinde uygulanmasına bağı ldır. Sonuç olarak, fosil yakıt sübvansiyonlarının kademeli olarak kaldırılmasını, karbon fiyatlandırma mekanizmalarının uygulanmasını ve çevre mevzuatının güçlendirilmesini içeren kapsamlı bir politika bileřimi, Akdeniz bölgesinde düşük karbonlu bir ekonomiye geçiřin güvenilir bir şekilde sağ lanması için kritik öneme sahiptir.

Keywords:

Climate Change,
Climate Finance,
Environmental Taxes,
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Green Finance.

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1. Introduction

The primary focus of economic policies worldwide remains sustaining economic growth, yet the adverse impacts of global warming and environmental degradation have already become widespread across many countries. Despite the concerns regarding the unsustainability of current production and consumption patterns, the global community has failed to provide a common and robust response to these concerns against strong economic growth goals. It is observed that resources are used unsustainably as a result of the desire for higher levels of production and consumption, as well as for rapid industrialization as part of countries' growth strategies.

Climate change is a pressing reality, scientifically proven and widely acknowledged. As stated by the Intergovernmental Panel on Climate Change (IPCC, 2013), "it is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century." Global greenhouse gas (GHG) emissions from the combustion of fossil fuels have increased extraordinarily since the onset of the Industrial Revolution. In 2022, the majority of global GHG emissions stemmed from carbon dioxide (CO₂), largely produced by burning fossil fuels (71.6%). Methane (CH₄) accounted for 21% of total emissions, with nitrous oxide (N₂O) making up 4.8%, and fluorinated gases (F-gases) comprising the remaining 2.6% (IEA- EDGAR, 2023).

According to the world CO₂ emissions statistics (IEA- EDGAR, 2023), GHG emissions released in the whole Mediterranean region were almost at the same level as those emitted by the EU27 countries as of 2022. While global GHG emissions reached 54 billion tonnes of carbon dioxide equivalent (CO₂e), emissions in the EU27 and Mediterranean have recently stabilized at around 3.1-3.6 billion tonnes. In the European Union (EU), GHG emissions per capita have been on a downward trend, with countries like Spain, Italy, and France contributing significantly to this decline (IEA- EDGAR, 2023).

The EIA (2021) reports that world energy-related CO₂ emissions were at a level of 34 billion metric tons as of 2020 and are projected to increase considerably throughout the years from 2020 to 2050. Energy-related CO₂ emissions are expected to surpass 40 billion metric tons by the year 2050. Taking a glance at their composition reveals that emissions from coal dominate all other sources in 2020 and will continue to be the major contributor to global energy-related emissions up to 2050. Emissions from coal are closely followed by those from liquid fuels. Emissions from natural gas make less than a third of the energy-related emissions throughout the inspected horizon (EIA, 2021). In addition to the GHG emissions caused by fossil fuel combustion and gas- or coal-fired power plants, there are other external costs of fossil fuel use in terms of environmental and health problems. Fossil fuels bear significant external costs, such as creating water, air, and soil pollution and deteriorating public health.

Addressing environmental challenges requires considering the differing circumstances of countries at various stages of development, as they exhibit significant variation in their levels of environmental degradation. Historically, high income countries have had much higher per capita GHG emissions than those of low and middle income countries. The Southern and Eastern Mediterranean countries and the Balkan countries in the Mediterranean are mostly composed of middle-income countries, whereas the EU members in the Mediterranean as well as Israel are mostly high-income countries. From an economic standpoint, the current trajectory of emissions has been a result of a combination of various policy tools such as taxes, subsidies, grants, loans, tax exemptions or reductions, financial instruments, and regulations. Conversely, a shift towards

sustainable practices is also achievable through a range of policies and strategies. Green finance represents one of these strategies aimed at facilitating the transition to a low-carbon economy.

This study¹ first aims to assess the economic policy implications of environmentally related taxes and feed-in tariffs (FiTs) utilized in Mediterranean countries concerning their impact on climate change. Second, it seeks to examine other green finance mechanisms employed and shed light on how they correlate with GHG emissions in the region. By doing so, the study seeks to evaluate the role and potential of green finance as a catalyst for advancing the transition to a low-carbon economy in the Mediterranean. This dual focus provides a comprehensive understanding of how economic tools and financial mechanisms can support sustainable development in the region.

The study offers several novel contributions. It is the first empirical analysis focusing specifically on the Mediterranean context that applies an econometric approach to assess the effectiveness of FiTs and climate-related taxes in reducing GHG emissions. It also accounts for the stringency of accompanying environmental policies, highlighting the conditions under which such tools become more effective. Through an evaluation of the broader landscape of green finance in the region, the paper sheds light on how different instruments interact to influence emission trends. This research is also particularly relevant given that the updated Mediterranean Strategy for Sustainable Development (MSSD 2026-2035)² led by UNEP/MAP, now places sustainable finance at the core of its approach. By providing evidence-based insights into how fiscal and financial instruments can support national and regional transitions, this paper directly contributes to advancing the MSSD's goals for sustainable, low-carbon Mediterranean economies.

The structure of the study is as follows: Section 2 undertakes a literature review on the implications of environmental finance policies for climate change outcomes and low-carbon transitions at country level. Section 3 aims to scrutinize the link between the selected finance mechanisms and per capita GHG emissions in Mediterranean states. Section 4 sheds light on the other green finance tools utilized in the region. Finally, Section 5 discusses the results, concludes and provides policy suggestions for the region.

2. Literature Review

Environmental taxation and renewable energy subsidies are pivotal tools in financing the transition to a green economy. These mechanisms leverage economic incentives to discourage environmentally harmful practices and foster sustainable development.

2.1. Environmental Taxation and Its Role in Emissions Reduction

Environmental taxes, in particular, target activities that generate negative externalities, such as carbon emissions, waste generation, and resource depletion, creating financial disincentives for damaging behavior.

¹ Building on the Acar (2025), it expands the analysis and contributes to academic engagement.

² The MSSD 2026–2035 is scheduled to be finalized and adopted by the end of 2025. After its mid-term evaluation, a draft update was prepared and reviewed by the Mediterranean Commission on Sustainable Development (MCSD) in February 2025, with final recommendations in June 2025, followed by formal adoption at COP 24 of the Barcelona Convention in December 2025.

Ma et al. (2018) use the environmental protection tax law in China as a case study to analyze how government tax oversight influences regional sustainable development, emphasizing the need for a robust green tax law system to achieve energy conservation and emission reduction goals while fostering green development. Similarly, Deng et al. (2022) argue that government tax policies play a critical role in shaping green development. Lv and Wu (2024) demonstrate that the reform of taxation systems has led to reduced carbon emissions in regions with stringent government environmental regulations as well as in regions with less stringent regulations in China. Furthermore, this transformation has facilitated regional green development overall. In the same vein, Chen et al. (2023) provide evidence that effective promotion of carbon emissions reduction hinges on leveraging the spatial effects of environmental taxes and carbon emissions in China. They advocate for establishing and enhancing a regional linkage mechanism for carbon emissions reduction, advocating for the inclusion of CO₂ within the taxation scope to bolster the positive impact of environmental taxes on reducing carbon emissions. Their research emphasizes the importance of addressing the diverse implementation approaches of environmental taxes to successfully achieve emission reduction objectives. Obobisa and Ahakwa (2024) find that renewable energy consumption, financial development, and environmental taxes contribute to the reduction of CO₂ emissions in 25 European countries, while Hao et al. (2021) and Xie and Jamaani (2022) detect a similar effect of environmental taxation on CO₂ emissions in G-7 countries (i.e. Canada, France, Germany, Italy, Japan, the United Kingdom and the United States). Khan et al. (2022), He et al. (2023), and Li et al. (2023) discover that environmental taxes and stringent environmental policies effectively decrease emissions in OECD countries. He et al. (2023) further demonstrate that an increase of one unit in environmental tax revenue per capita leads to a decrease of 0.02% in CO₂ emissions across OECD countries. Sarigul and Topcu (2021) as well as Akkaya and Hepsag (2021) detect that environmental taxes and fuel taxes have a negative impact on CO₂ emissions in Türkiye.

However, Zhu et al. (2023) critique overly optimistic assumptions, noting that regional disparities in regulations may lead to emissions shifting to jurisdictions with less stringent policies, thereby undermining the overall effectiveness of environmental taxes.

2.2. Renewable Energy Subsidies and Feed-in Tariffs

Renewable energy subsidies, such as feed-in tariffs (FiTs), represent another critical policy tool to accelerate the transition to a low-carbon economy. By facilitating the substitution of fossil fuels with renewable energy, they are expected to contribute to emissions reduction. One such measure is feed-in tariffs (FiT), which consists of fixed payments per kilowatt-hour (kWh) established by an administrative authority, typically offered to eligible energy producers. The FiT effectively subsidizes renewable energy generation by covering the difference between the market price of electricity and the tariff's value. Without such subsidies, renewable generators would sell their electricity on the wholesale market, where prices fluctuate based on market conditions at the time of generation. FiTs offer generators a predictable income through a fixed price for their entire output, which acts as a subsidy if this tariff exceeds the wholesale price. This subsidy is quantifiable by comparing FiTs with wholesale prices. Moreover, the certainty provided by the tariff reduces revenue risk associated with fluctuations in wholesale prices. FiTs help accelerate the adoption of renewable energy technologies by guaranteeing renewable energy producers a stable, long-term purchase price for the electricity they produce. This financial incentive provides

a predictable revenue stream that reduces investment risks and encourages private sector participation in renewable energy projects. FiTs are expected to facilitate the financing of the green economy by attracting investments in renewable energy infrastructure, such as solar, wind and biomass systems, and encourage the growth of sustainable energy markets.

There are a range of subsidies granted to renewable energy in many countries. Qi et al. (2023) investigate the temporal alignment of an emissions trading system (ETS) and FiTs for solar and wind energy projects in China, emphasizing the impact of subsidy strategies. Their research indicates that continuous FiT subsidies have a more positive overall effect compared to phasing them out. They highlight that introducing FiT can ease the burden and cost of reducing emissions under the carbon ETS. During the FiT subsidy period, higher subsidy rates correspond to reduced pressure for emission reductions within the carbon ETS framework. Similarly, Lin and Xie (2024) discover that a one-unit increase in FiT subsidies correlates with a 3.4-unit rise in renewable energy investments, based on firm-level data from China. Mardones (2024) demonstrates in the case of Chile that integrating three climate policies—carbon taxes, coal-fired power plant phase-out, and renewable energy subsidies—leads to a significant decrease in GHG emissions, using a computable general equilibrium model and microsimulations.

The Mediterranean warrants distinct analytical attention for several reasons. First, it is recognized by the IPCC as a climate hotspot, warming faster than the global average and facing acute risks such as droughts, water scarcity, and sea-level rise. Second, the region combines high dependence on fossil fuel imports with abundant but underutilized renewable energy potential, making the design and financing of green finance policies especially consequential. Third, the Mediterranean spans a diverse set of economies—from EU member states like Italy and Spain to emerging economies in North Africa and the Balkans—creating a natural laboratory to examine how environmental taxes, subsidies, and policy stringency operate under heterogeneous institutional and financial conditions. Finally, the region’s strategic role in EU climate and energy policy, including the European Green Deal and cross-Mediterranean renewable energy initiatives, further underscores the geopolitical importance of effective green finance mechanisms. Despite these distinctive features, systematic empirical assessments of green finance tools in the Mediterranean remain scarce, which justifies the regional focus of this study. Most analyses center on global, or national contexts, overlooking the region’s specific economic and policy dynamics. Few studies combine environmental taxes, feed-in tariffs, and policy stringency within a single econometric framework. This paper fills that gap by providing one of the first empirical assessments of green finance tools and their impact on GHG emissions in Mediterranean countries, using a unique dataset and a consistent panel data approach. The findings offer practical insights for regional sustainability efforts.

3. Data, Method, and Analysis: The Link Between Environmentally Related Taxes, FiTs, and GHG Emissions in Mediterranean Countries

Making use of the relevant indicator definitions and data, the following research questions are answered in this section:

1. Which countries in the Mediterranean region tax the production or consumption of environmentally related goods and services more highly in the region?

2. Does environmental taxation make a significant difference in per capita GHG emissions in the region?

3. Which energy source is supported more by the FiT incentives in the region?

4. Does the type of renewable energy source subsidized make a significant difference in per capita GHG emissions in the region?

Section 3.1 undertakes a thorough review of environmentally related taxes and FiTs provided to renewable energy in the Mediterranean countries, whereas Section 3.2 explores the links between these policies and per capita GHG emissions in the region using an econometric approach.

3.1. Data: Environmentally Related Taxes and FiTs in the Mediterranean

Environmentally related taxes play a crucial role for governments in influencing the prices of goods and services. The OECD Environmentally Related Tax Revenue Database (ERTR) classifies taxes according to their environmental impact, using a structured method to compile revenue specifically from environmentally related taxes. This includes detailed categorization by tax-base types such as energy, transport, pollution, and resources, across 22 environmental domains. ERTR is constructed by 1) focusing on taxes on GHG emissions from different activities by splitting tax revenues into two subcategories: the energy-related part (recorded as an energy tax) and the non-energy-related part, such as certain GHG emissions from landfills or agriculture (recorded as a pollution tax), and 2) introducing four "memo items" to enhance the relevance of the accounts for policy work: (i) certain land taxes, (ii) taxes on oil and natural gas extraction, (iii) taxes on the resource rent (profit taxes only) and (iv) elevated VAT levied on environmentally related tax bases (OECD, 2023).³

As shown in Figure 1, in 2019, Croatia, Slovenia, and Greece led the Mediterranean region in the share of GDP allocated to environmental taxes, covering areas like carbon emissions, waste generation, and resource depletion. Conversely, countries from the South Mediterranean such as Morocco and Egypt appear to have allocated a smallest proportion of their GDP to environmental taxation. When considering tax revenue per capita (measured in 2015 USD PPP), Slovenia, Italy, Croatia, and Greece rank as the highest tax-collecting countries (OECD, 2023).

³ For robustness checks, we employ the environmentally related tax revenue in the domain of climate change (% of GDP) as the main independent variable in two model specifications in Section 3.2.

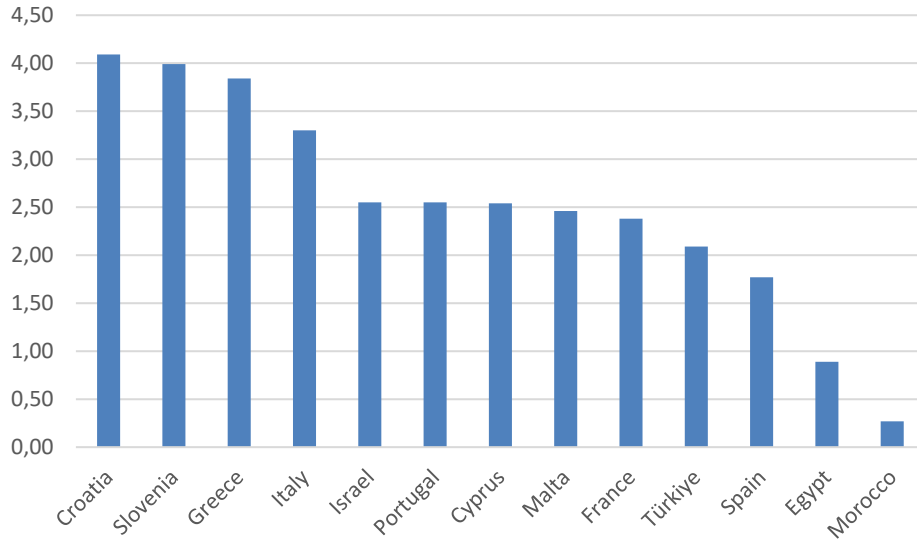


Figure 1. Environmental Taxation (% of GDP) in the Region, 2019

Source: Author's illustration using OECD (2023) data

According to the “Environmental Policy: Renewable energy feed-in tariffs” database of the OECD (Edition 2021), FiTs are widely used policies designed to promote the expansion of renewable electricity capacity. These market-driven economic tools generally provide long-term agreements that ensure a fixed price per kilowatt-hour (kWh) for electricity supplied to the grid from a specified energy source. OECD (2022) reports both the mean FiT prices (in USD) and the length of power purchase agreements (in years) for each renewable source supported. The length of agreements ranges between 10 and 25 years. In the Mediterranean region, almost every country has implemented a FiT policy, except for Malta and Morocco. As a small island nation, Malta has limited land and natural resources, making large-scale renewable energy deployment difficult. Solar and wind are the most viable options, but land scarcity and high population density restrict the deployment of large solar farms or wind projects. This explains why it may not be preferred to implement a FiT policy in Malta. While Morocco has abundant solar and wind resources, its focus has historically been on large-scale centralized renewable projects such as Noor Ouarzazate (one of the world's largest solar power plants)⁴. The government may view FiT policies as less compatible with its central development strategy. Besides, FiT policies often require long-term subsidies or guaranteed purchase agreements, which can be a burden on national budgets or lead to higher energy prices for consumers. For countries like Morocco, where affordability and energy access are priorities, FiTs might not be the optimal choice. Also, competitive bidding or auctions for renewable energy projects, which allow investors to control costs better compared to FiTs, can attract large-scale investors by providing a predictable framework in countries like Morocco.

Based on Figure 2, the number of countries adopting FiTs in the Mediterranean region reached a total of 13 in year 2012 and afterwards started to decline. As of 2019, there were only three countries (France, Italy, and Türkiye) in the region that provided FiT support to one or more renewable resources. Among them, FiTs in France were the highest, with 0.094 USD/kWh to small hydro, 0.16 USD/kWh to waste, and 0.14 USD/kWh to marine power in 2019. Historically,

⁴ <https://ouarzazate.city/noor-ouarzazate-solar-power-station/>

some countries provided higher FiT prices to solar power per kWh of electricity (e.g. Cyprus and Greece) while countries such as Türkiye provided the lowest prices (OECD, 2022). Feed-in tariffs in Türkiye also benefit from local content premiums depending on the renewable energy technology.⁵

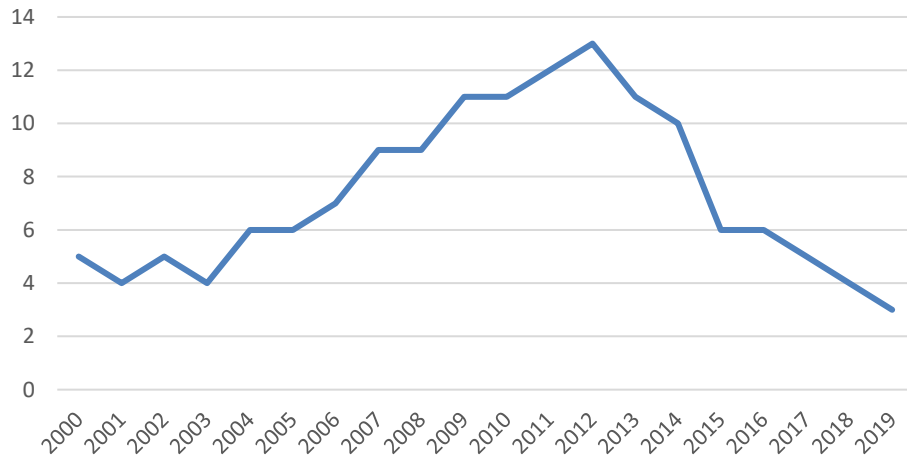


Figure 2. Number of Countries Adopting FiTs in the Region
Source: Author’s illustration using OECD (2022) data

Figure 3 shows the decline in countries offering FiT support for renewable energy sources from 2012 to 2019. In 2012, the peak year, 10 countries supported solar, 11 wind, and 10 small hydro, among other resources.

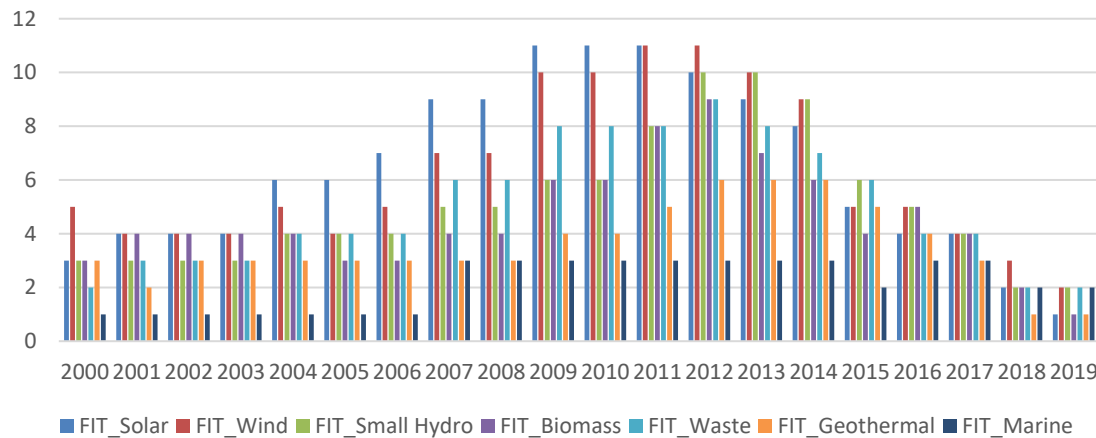


Figure 3. Number of Countries with FiTs with Respect to Source
Source: Author’s illustration using OECD (2022) data

By 2019, this had dropped to just 1 for solar, 2 for wind, 2 for small hydro, and 1-2 for other resources. This decline can be attributed to several factors: As solar and wind technologies

⁵ Türkiye also advances renewable energy through YEKAs (Renewable Energy Resource Areas), which are legally designated zones aimed at fostering substantial renewable electricity capacity and promoting localization in renewable energy technologies.

became more cost-competitive (IRENA, 2024), the need for FiTs decreased. Many countries also shifted from FiT schemes to competitive auctions, which reduce costs through competition (Mathieu and Valenzuela, 2024). Additionally, governments increasingly favored alternative support mechanisms like tax credits, subsidies, and green certificates, which offer more flexibility and lower costs (Del Rio and Linares, 2014). Countries like Italy, Spain, France, Greece, Morocco, Tunisia, and Egypt have adopted such market-based approaches to encourage renewable investment while reducing financial burdens on public budgets and consumers.

3.2. Methodology and Results

This section examines the causal relationship between GHG emissions per capita and two key environmental policy tools in the Mediterranean region. Specifically, it analyzes:

- The effect of environmentally related taxes on GHG emissions from 1994 to 2021.
- The effect of Feed-in Tariffs (FiTs) on GHG emissions from 2000 to 2019.

The analysis uses panel data methods to explore these relationships.

The data for environmentally related tax revenue (% of GDP) for the period 1994-2021 and FiTs (USD) for the period 2000 – 2019 are extracted from the OECD database, whereas per capita GHG emissions (*GHGPC*) data (tonnes CO₂e/year) is extracted from the IEA and Emissions Database for Global Atmospheric Research (EDGAR) constructed by Crippa et al. (2023). GHG emissions in the IEA-EDGAR database include CO₂ (fossil only), CH₄, N₂O and F-gases and are aggregated using Global Warming Potential (GWP) values from IPCC AR5 (GWP-100 AR5). GDP per capita (purchasing power parity-adjusted, constant 2021 international USD), renewable electricity output (% of electricity production) and fossil fuel energy consumption (% of total) are used as control variables in explaining per capita emissions in each country. Economic expansion is positively correlated with increased energy consumption, which, in turn, elevates GHG emissions, particularly in countries that predominantly depend on fossil fuel-based energy infrastructures. The generation of renewable electricity (*REO*) is anticipated to mitigate per capita GHG emissions, whereas fossil fuel energy consumption (*FOSSIL*) is projected to have the opposite effect, contributing to increased emissions. A higher proportion of renewable energy sources in electricity generation directly diminishes emissions attributed to fossil fuel combustion. Renewable energy technologies, including solar, wind, and hydroelectric power, do not produce carbon emissions during their energy conversion processes, thereby reducing overall emission intensity. Concurrently, the declining levelized cost of electricity (LCOE) for renewable energy technologies promotes their broader adoption, further enhancing their potential to mitigate emissions.

In order to test whether policy stringency plays a role and affects the effectiveness of environmental taxation, the OECD Environmental Policy Stringency Index (EPS) is used in several equations as well (Kruse et al., 2022). The EPS index is a country-specific and internationally comparable measure of the stringency of environmental policy ranging from zero (least stringent) to six (most stringent). The index covers the years from 1990 to 2020, across 40

countries and 13 policy instruments, focusing on climate change and air pollution mitigation policies.⁶

The econometric analysis uses panel data, which tracks the same countries over multiple years. This allows for the analysis of both cross-country variations and time-series trends. Panel data analysis helps control for individual differences between countries, ensuring that the relationship between environmental policies and emissions is not obscured by other factors. The panel structure of the data used in this study enables to examine the effects of environmentally related policies on GHG emissions per capita both on a country level and over a time span (1994-2021). Panel data analysis facilitates the control of individual heterogeneity by allowing for the examination of variation and involving less linear correlation between variables. Besides, a fixed effects specification is selected in order to control for variables that are constant within each entity (such as a country), but vary between entities.⁷ It allows us to estimate the impact of variables that change over time (e.g., tax revenues) while accounting for unobserved characteristics that could differ between countries but do not change over time (such as institutional frameworks). In simpler terms, it helps isolate the effects of changes in specific variables by controlling for other factors that might influence the results. The model can be expressed as follows:

$$y_{it} = \alpha + X_i' \beta + u_{it} \quad (1)$$

In Equation (1), for $i = 1, \dots, N$ and $t = 1, \dots, T$, where y_{it} is the dependent variable, X_i' is the vector of independent variables, β is the coefficient vector of independent variables, and u_{it} is the composite error. In the current analysis, heteroskedasticity-corrected standard errors are estimated using the robust estimator of the covariance matrix proposed by Arellano, which take into account both heteroskedasticity and autocorrelation. By incorporating country-fixed effects (to control for time-invariant unobserved heterogeneity) and time-fixed effects (to capture global shocks like economic crises or climate agreements), our methodology helps mitigate confounding. Furthermore, the inclusion of fixed effects helps mitigate omitted variable bias. Additionally, our regressions might suffer from reverse causality, which implies that higher GHG emissions per capita might drive policy responses, rather than environment/climate policies influencing emissions. This issue can be handled by using lagged independent variables to ensure that the explanatory variables precede the outcome (GHG per capita), reducing simultaneity bias. Models 1a.i to 2b.ii in the Appendix present the results of the regressions with lagged values of renewable electricity output, fossil fuel consumption, and environment/climate policies, which provide similar results to those presented in Table 1. To maintain a broader dataset without omitting data for any given year, we base our interpretations on the results presented in Table 1.

Table 1 presents the fixed effects estimation results in four separate models that include two environmental tax categories as explanatory variables. Model 1a and 1b integrates the effects of total environmental tax revenue (*ENVTAX*) (at all tax bases as a % of GDP) on the natural logarithm of *GHGPC*, whereas Models 2a and 2b integrate the effects of environmental tax revenue in the domain of climate change (*CLIMTAX*) (as a % of GDP). Models 1a and 2a include *REO*, renewable electricity output (% of electricity production), whereas Models 1b and 2b

⁶ The structure of the EPS, its components and the index construction can be accessed in the related 2022 OECD working paper: <https://doi.org/10.1787/90ab82e8-en>

⁷ The fixed effects specification is chosen for the analysis because the Hausman (1978) test results indicate that the null hypothesis (which asserts that GLS estimates are consistent) is rejected. This rejection implies that the random effects estimator is inconsistent, making fixed effects the appropriate approach.

include *FOSSIL*, fossil fuel energy consumption (% of total) as well as *EPS* in interaction with the tax variables.

Table 1. Fixed Effects Estimation Results for Environmental and Climate Taxation

	Model 1a	Model 1b	Model 2a	Model 2b
	LNGHGPC	LNGHGPC	LNGHGPC	LNGHGPC
Variable	Coefficient	Coefficient	Coefficient	Coefficient
	(Standard Error)	(Standard Error)	(Standard Error)	(Standard Error)
LNGDPPC	0.60*** (0.09)	0.51*** (0.05)	0.61*** (0.09)	0.50*** (0.05)
REO	-0.005*** (0.001)		-0.005*** (0.001)	
FOSSIL		0.02*** (0.002)		0.02*** (0.002)
ENVTAX	-0.004 (0.012)	-0.03** (0.012)		
CLIMTAX			0.0009 (0.011)	-0.03** (0.01)
EPS		-0.03*** (0.012)		-0.04*** (0.009)
EPS*ENVTAX		0.01*** (0.003)		
EPS*CLIMTAX				0.02*** (0.002)
constant	-4.06 (0.91)	-4.65*** (0.38)	-4.15*** (0.91)	-4.60*** (0.43)
time dummies	yes	yes	yes	yes
observations	350	175	352	176
LSDV R-squared	0.96	0.98	0.96	0.98

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Models 1a and 2a reveal that an increase in the share of country-level environmental tax revenue or climate-related tax revenue in GDP does not significantly affect GHG emissions per capita in the region. Once these two tax variables enter the equation in interaction with environmental policy stringency (*EPS*), taxation decreases GHG emissions significantly (Models 1b and 2b). A 1 percentage point increase in *ENVTAX* or *CLIMTAX* leads to a net decline of 0.01-0.02% in *GHGPC*. This implies that environmental taxes alone may not be set at levels high enough to significantly change behavior, especially if the cost of compliance is lower than the economic benefits of continuing high-emitting activities. However, strict environmental policies increase the effectiveness of taxes by creating additional pressure to adopt cleaner technologies and practices. Besides, taxes often work best when paired with complementary policies, such as emissions standards, renewable energy mandates, or energy efficiency incentives. Policy stringency likely reflects the existence of such measures that enhance the impact of taxation by providing multiple, reinforcing mechanisms to reduce emissions. In the absence of strict enforcement, tax policies may be missed or fail to achieve their intended effect. Strict policies are more likely to include robust enforcement measures that ensure that taxes are effectively implemented and their behavioral objectives are achieved (see the country examples such as

France and Italy, where EPS has risen during the investigated time period and per capita GHG emissions are on a considerable decline).

To sum up, environmental taxation, alone, while an effective tool for internalizing the environmental costs of economic activities, may fail to significantly accelerate the low-carbon transition due to several limitations such as insufficient tax rates, policy design flaws, economic and political resistance, regressive impacts on low-income populations, and the risk of carbon leakage. Additionally, taxation alone cannot fully address the structural and behavioral changes needed for a low-carbon economy without complementary measures like subsidies, infrastructure investments, and stringent regulations. When combined with strict environmental policies, taxation becomes more effective and leads to measurable emissions reductions. This suggests that strict regulations increase the impact of taxes by encouraging cleaner technologies and discouraging high-emitting activities. To maximize its impact, environmental taxation should be integrated into a broader policy framework that addresses these challenges holistically by including renewable energy subsidies, infrastructure investments, and regulatory enforcement. In addition, earmarking tax revenues for climate action (such as financing renewable energy projects and energy efficiency programs) can increase their effectiveness. Targeting high-emitting sectors specifically rather than broad-based taxes can also lead to more significant reductions.

In the same analysis above (Table 1), GDP per capita makes a significant contribution to emissions per capita; i.e. being a wealthier country in average per capita terms implies an increase in the GHG each person emits on average. To be more precise, a 1% increase in *GDPPC* leads to a 0.5-0.6% increase in emissions per capita. On the other hand, renewable energy output, *REO*, contributes to the low-carbon transition significantly as it decreases emissions by 0.005% as *REO* increases by 1 percentage point. Higher shares of fossil fuel consumption, *FOSSIL*, contributes to increasing per capita emissions, as expected.

Table 2 presents the results of fixed effects analyses examining the factors influencing emissions across four different models. Each model focuses on how different types of Feed-in Tariffs (FiTs) affect emissions.

Models 3a and 3b analyze whether simply having a FiT policy (*FIT_DUMMY*) in place in a given country and year impacts emissions.

Models 4a and 4b go a step further by examining the specific *FiT prices* offered for different renewable energy sources, including solar, wind, hydro, biomass, waste, geothermal, and marine energy.

Additionally, these models differ in the control variables they include:

Models 3a and 4a control for economic activity (log of GDP per capita, *LNGDPPC*) and renewable electricity output (*REO*).

Models 3b and 4b instead control for economic activity (*LNGDPPC*) and fossil fuel consumption (*FOSSIL*).

This approach allows us to compare the effects of having FiT policies versus the specific price incentives they provide, while also accounting for key economic and energy-related factors.

Table 2. Fixed Effects Estimation Results for FiTs

	Model 3a	Model 3b	Model 4a	Model 4b
	LNGHGPC	LNGHGPC	LNGHGPC	LNGHGPC
Variable	Coefficient (Standard Error)	Coefficient (Standard Error)	Coefficient (Standard Error)	Coefficient (Standard Error)
LNGDPPC	0.64*** (0.10)	0.78*** (0.05)	0.62*** (0.11)	0.79*** (0.05)
REO	-0.005*** (0.001)		-0.005*** (0.001)	
FOSSIL		0.01*** (0.003)		0.01*** (0.003)
FIT_DUMMY	-0.0007 (0.003)	0.0009 (0.003)		
FIT_SOLAR			-0.01 (0.03)	-0.004 (0.014)
FIT_WIND			0.02 (0.04)	0.005 (0.024)
FIT_HYDRO			-0.11** (0.05)	-0.07* (0.04)
FIT_BIOMASS			0.27* (0.15)	0.20 (0.13)
FIT_WASTE			-0.09*** (0.03)	-0.04** (0.02)
FIT_GEOTHERMAL			-0.02 (0.09)	-0.07 (0.08)
FIT_MARINE			-0.08** (0.04)	-0.0006 (0.04)
constant	-4.71*** (1.07)	-7.26*** (0.38)	-4.45*** (1.19)	-7.14*** (0.37)
time dummies	yes	yes	yes	yes
observations	280	231	280	231
LSDV R-squared	0.96	0.99	0.96	0.99

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Models 3a and 3b reveal that providing feed-in-tariffs (i.e. the presence of a FiT scheme to any renewable source) alone does not significantly affect GHG emissions per capita in the region. It is a well-known fact that FiTs might be effective in promoting renewable energy but face limitations such as high financial burdens, inefficiencies in targeting emerging technologies, market distortions, and grid integration challenges. By guaranteeing fixed prices, FiTs can potentially distort energy markets, discouraging competition and innovation. Over-reliance on FiTs may also slow the transition to market-based mechanisms like auctions or competitive pricing, which can drive cost efficiencies in renewable energy deployment. Policy instability and regional disparities can further hinder their effectiveness, while their focus on electricity generation often neglects other critical sectors like transportation or industry. Additionally, the long timeframes for renewable infrastructure development may delay significant emission reductions. To enhance their impact, FiTs need to be part of a broader strategy that includes grid modernization, energy storage, carbon pricing, and measures to ensure equity and regional inclusivity.

Once the FiT prices (USD per kWh) to each renewable source are accounted for (Models 4a and 4b), 1 USD increase in FiT prices provided to hydro, waste and marine power decreases GHG emissions per capita significantly (Model 4a). The coefficients of FiTs to waste and hydro appear to be significant in Model 4b as well, once *FOSSIL* is used as a control variable. On the other hand, a 1-USD increase in *FIT_BIOMASS* increases *GHGPC* by around 0.3%.

The difference in the impacts of FiT prices on GHG emissions reductions among renewable energy sources in Mediterranean countries can be attributed to several factors: The first one is related to the baseline energy mix. Hydro, waste, and marine power often displace high-emission, base-load energy sources like coal or oil-fired plants, leading to more substantial reductions in GHG emissions. On the other hand, solar, wind, and geothermal may replace less carbon-intensive energy sources, such as natural gas, or contribute to intermittent generation that doesn't fully offset fossil fuel dependency. Second, hydro, waste-to-energy, and marine power typically have higher capacity factors (i.e., they generate electricity more consistently) compared to solar and wind, which are intermittent and dependent on weather conditions. Consistent generation ensures a more stable replacement of fossil fuel-based energy, resulting in greater GHG reductions. Geothermal energy has high reliability but may have limited implementation due to geological constraints in Mediterranean countries (for example, in countries like Algeria, Egypt, and Morocco, geothermal has limited implementation due to the absence of significant tectonic activity). Third, in regards to infrastructure needs, hydro, waste, and marine power are often integrated into existing grid systems more effectively, leading to immediate and sustained reductions in emissions; whereas solar and wind power may face challenges like curtailment due to grid constraints or a lack of storage solutions, reducing their net impact on emissions. Fourth, hydro, waste, and marine projects often involve large-scale installations that can significantly impact national energy mixes. On the contrary, solar and wind installations in Mediterranean countries may be smaller-scale (Türkiye being an exception in this regard), distributed systems that individually contribute less to GHG reductions.

FiT prices provided to biomass energy might inadvertently trigger an increase in GHG emissions per capita in Mediterranean countries due to several factors: To begin with, if biomass feedstocks (e.g., wood, agricultural residues, or organic waste) are sourced unsustainably, such as through deforestation or overharvesting, the carbon released during combustion may exceed the carbon sequestered during the biomass's growth cycle, leading to a net increase in GHG emissions. Besides, transportation and processing of biomass can also generate significant emissions, particularly if local supply chains are not well-developed. Furthermore, older or poorly maintained biomass power plants may operate with low energy conversion efficiencies, resulting in higher emissions per unit of energy produced (for instance, the biomass power plants in Greece (Alatzas et al., 2019), Türkiye (Ocak and Acar, 2021), and Italy (Moliner et al., 2021) still use older combustion technologies or are not optimized for efficiency). Incomplete combustion of biomass can release methane, carbon monoxide, and black carbon, all of which are potent contributors to global warming.

In the same analysis (Table 2), GDP per capita makes a significant contribution to emissions per capita by leading to a 0.6-0.8% increase in *GHGPC* as a result of 1% increase in *GDPPC*. A 1 percentage point increase in *FOSSIL* triggers *GHGPC* by 0.01%. On the other hand, as in Models 1a and 2a, renewable energy output, *REO*, contributes to the low-carbon transition significantly as it decreases emissions by 0.005% as *REO* increases by 1 percentage point.

Alternative methods such as system GMM, instrumental variables, or quasi-experimental approaches (e.g., difference-in-differences, event studies) can strengthen causal identification under the right conditions. Yet, given our dataset—a moderate number of Mediterranean countries observed over a long time horizon—fixed effects estimation offers the most reliable framework. IV approaches are constrained by the scarcity of strong exogenous instruments in cross-country green finance research, while DID methods face difficulties in this context due to heterogeneous policy adoption and the challenge of satisfying parallel trend assumptions. Therefore, the fixed effects framework represents a rigorous and widely accepted methodology for our research question.

4. How to Finance the Low-Carbon Transition Through Other Types of Green Finance?

Carbon pricing—through emissions trading schemes (ETS) or carbon taxes—is one of the most widely used policy instruments to reduce greenhouse gas emissions by internalizing their social cost (Nordhaus, 2014; Tietenberg and Lewis, 2018). Yet, in practice, carbon markets often fail to reflect the true marginal cost of emissions reductions, with prices remaining volatile and frequently too low to drive long-term investment shifts (ERCST, 2021). The EU Emissions Trading System (EU ETS), which applies to Mediterranean EU member states, illustrates this tension (Figure 4).

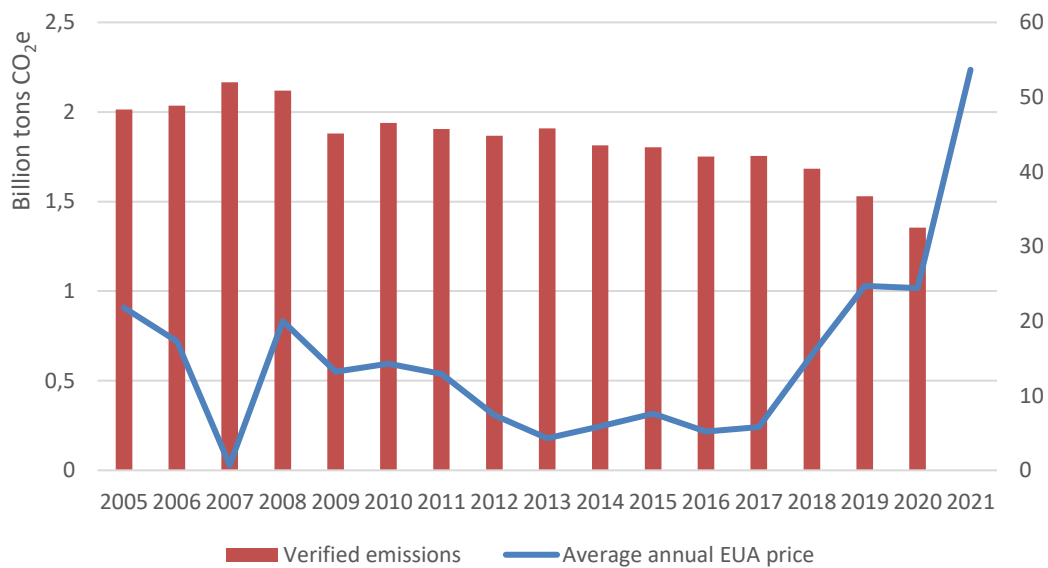


Figure 4. Average Annual EUA Prices (Euro/ton) and Verified Emissions (billion tons CO₂e)
Source: EEA (n.d.) EU Emissions Trading System Data Viewer & Ember (n.d.) Climate Carbon Price Viewer

While verified emissions have declined—most notably in the electricity sector, where reductions reached nearly 28% between 2013 and 2019—evidence suggests more limited abatement in other covered sectors (Martin et al., 2016; Pellerin-Carlin and Vangenechten, 2022). The performance of the EU ETS in Mediterranean countries therefore remains mixed and difficult

to assess at the macro level, as sectoral and firm-level impacts are uneven. One tangible benefit, however, has been the revenue generated through allowance auctions, much of which is earmarked for climate and energy investments. In 2022, for example, most Mediterranean EU member states allocated nearly all of their auction revenues to such purposes, though Italy notably directed only half (EEA, 2023). These variations underscore why it is important to empirically assess whether carbon pricing mechanisms have delivered measurable emission reductions across Mediterranean economies—something that remains underexplored in the literature. While carbon pricing seeks to influence emissions through market-based incentives, complementary green finance instruments—such as green bonds, loans, and central bank initiatives—directly channel investment toward low-carbon projects, addressing gaps that carbon pricing alone may not resolve. Globally, the green bond market has expanded rapidly since 2007, with proceeds primarily allocated to energy, buildings, and transport (CBI, 2022; also see Figure 5 below). Yet concerns about “greenwashing” persist, as some issuances finance projects with limited or even negative climate benefits (Rajwanshi, 2019). Green loans face similar criticisms, while their distribution remains heavily skewed toward developed markets, leaving developing countries with only a marginal share of issuances (IFC, 2021). These challenges highlight the need for robust transparency and reporting standards if such instruments are to genuinely accelerate the green transition.

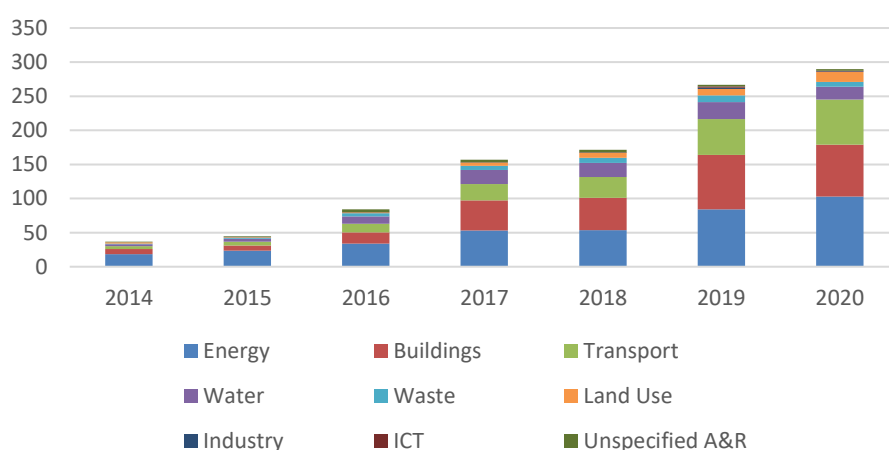


Figure 5. Sectoral Use of Proceeds from Climate Bonds (issued billion USD)
Source: Climate Bonds Initiative (CBI, 2022)

In the Mediterranean, the development of green finance markets is uneven. Northern Mediterranean countries, particularly France and Italy, are among Europe’s leading issuers, while Southern and Eastern Mediterranean countries have only recently entered the market. Notable milestones include Turkey’s first green bond issuance in 2016 and Egypt’s launch of the MENA region’s first sovereign green bond in 2020 (TSKB, 2017; Hussain, 2022). Central banks in the region are also beginning to integrate sustainability into their mandates, with the Central Bank of Egypt issuing guidelines for sustainable finance in 2021 (American Chamber of Commerce in Egypt, 2023). These steps suggest growing momentum, but the scale remains modest compared to Northern peers.

The banking sector plays a pivotal role in this landscape, serving as the primary channel for financing the real economy. While green loans are growing globally—reaching \$56.8 billion in the US and \$1.4 billion in Italy in 2021 (World Bank, 2021)—their uptake across much of the Mediterranean remains limited. This divergence underscores a critical gap: while the region faces urgent climate risks, its financial capacity to support the green transition varies widely across national contexts. For this reason, in future studies, it is essential to empirically evaluate whether and how these green finance instruments have contributed to emission reductions across Mediterranean economies, rather than assuming global trends translate automatically to regional outcomes.

While green bonds, loans, and central bank initiatives mobilize domestic and regional capital for low-carbon projects, multilateral development banks (MDBs) and climate funds play a complementary role by providing large-scale financing and technical support, particularly in Mediterranean countries where private and public resources for the green transition remain limited. In the Mediterranean, initiatives such as the Clean Technology Fund and the World Bank have supported renewable energy and efficiency projects—for example, in Türkiye, where financing has contributed to the installation of nearly 1 GW of renewable capacity and significant emission reductions (Fosse et al., 2017). Among MDBs, the European Bank for Reconstruction and Development (EBRD) is especially influential: in 2023, half of its portfolio (€6.5 billion) was allocated to green finance, with Türkiye consistently among its major recipients (Bitsadze, 2024). Other European institutions, including the Council of Europe Development Bank and the French Development Agency, have also provided important funding streams.

The distribution of multilateral climate finance, however, is highly uneven across Mediterranean countries. While France and Italy have historically attracted the largest shares of MDB outflows, other EU members such as Greece, Portugal, and Spain have received minimal inflows (Bos and Thwaites, 2021; also see Figure 6 below). This divergence suggests that access to multilateral finance depends not only on need, but also on institutional capacity, creditworthiness, and alignment with donor priorities. Such disparities are particularly important for the Mediterranean, where domestic fiscal space and capital markets are often insufficient to meet investment needs for the green transition.

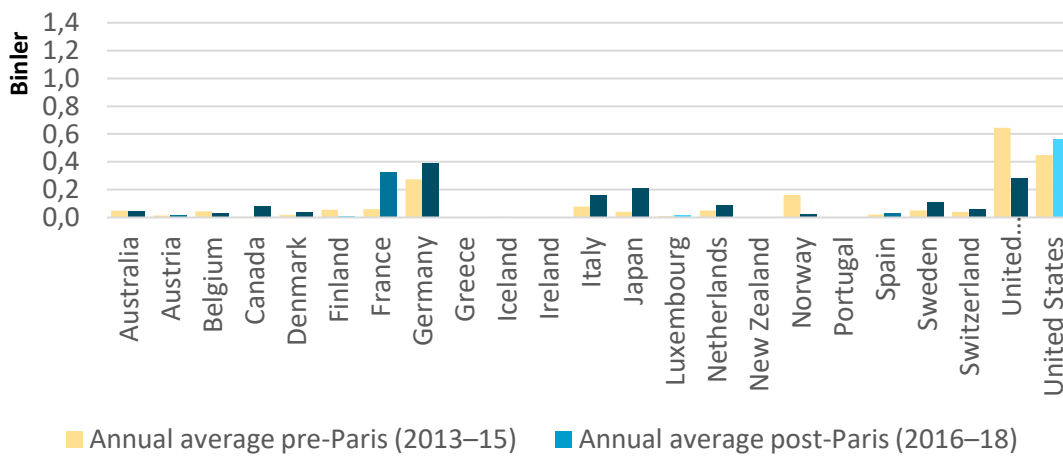


Figure 6. Multilateral Climate Finance Inflows (excluding MDBs) by Country, Annual Average Pre- and Post-Paris Agreement

Source: Bos and Thwaites (2021), World Resources Institute.

These observations highlight the importance of considering multilateral finance as part of the broader green finance landscape in the region. Yet the lack of consistent long-term data makes it difficult to evaluate systematically whether MDB funding has translated into measurable reductions in greenhouse gas emissions—reinforcing the need for empirical assessments such as the one undertaken in this study.

In sum, carbon pricing, green finance instruments, and multilateral funding initiatives represent three complementary avenues for advancing the green transition in the Mediterranean. Yet, each faces challenges: carbon markets remain volatile and uneven in their sectoral impact; green bonds and loans are expanding but subject to risks of greenwashing and unequal distribution; and multilateral finance flows, while critical for countries with limited fiscal space, are highly concentrated in a few recipients. What unites these mechanisms is both their potential to reshape investment patterns and their uneven performance across the region’s diverse institutional, financial, and economic contexts. Despite their growing prominence, there is little systematic evidence on how these tools have translated into measurable emission reductions at the regional level. This gap highlights the importance of future research pathways, which could offer empirical assessments of green finance tools and their effectiveness in reducing GHG emissions across Mediterranean economies.

5. Conclusion and Policy Recommendations

Leaning upon our empirical findings, green taxation significantly matters, on condition that policies are stringent enough to enforce measures that ensure that taxes are effectively implemented. For instance, in countries such as France and Italy, rising EPS values during the period of analysis coincided with a measurable decline in per capita emissions, illustrating how policy stringency amplifies the effect of taxation. By contrast, in Southern and Eastern Mediterranean countries, where tax revenues as a share of GDP remain below 1% and EPS scores are low, the impact of such taxes has been negligible.

Besides, revenues from environmental taxes can be strategically allocated to finance renewable energy projects, energy efficiency programs, sustainable infrastructure, and research and development in green technologies. In addition, such taxes can support subsidies or grants for clean energy adoption, offsetting transition costs for businesses and households. By internalizing environmental costs into market prices, environmental taxation may not only promote resource efficiency, but also encourage innovation and investment in sustainable industries, thereby accelerating the transition to a low-carbon economy.

Sectoral targeting in environmental taxation also matters. Taxes should focus on the Mediterranean’s most emissions-intensive sectors—transport fuels, cement, and shipping—rather than being applied in a diffuse, economy-wide manner. Revenues could be earmarked for investments in public transport electrification (relevant for North African cities) or for retrofitting energy-intensive industries (relevant for Southern Europe). Environmental taxes need to be designed in a way to target the most emissions-intensive sectors effectively instead of being broadly applied. When combined with stringent policies that focus on high-impact areas (e.g., heavy industry, transportation), the interaction may drive more substantial emissions reductions.

FiTs are a policy mechanism designed to accelerate the adoption of renewable energy technologies by guaranteeing renewable energy producers a stable, long-term purchase price for

the electricity they produce. This financial incentive provides a predictable revenue stream that reduces investment risks and encourages private sector participation in renewable energy projects. However, as observed through the econometric analysis, the implementation of FiTs does not always guarantee the acceleration of a low-carbon transition. Our econometric results indicate that FiTs are most effective when directed at hydro, waste-to-energy, and marine power, while FiTs for biomass correlate with higher emissions. This is consistent with evidence from the literature, where inefficient biomass combustion technologies have increased net emissions. Moreover, France stands out as a country with relatively high FiTs for hydro, waste, and marine energy, illustrating the potential for well-targeted tariffs to drive emission reductions.

FiTs can promote renewable energy production in an economic environment which also prioritizes a reduction in dependence on fossil fuels and reducing GHG emissions. When there are contradictory energy policies in place, FiTs may not end up with the desired outcomes they are meant to lead to. On the one hand, subsidies to renewable energy can be justified as they support infant renewable energy industries in the early stages of their development and spread. On the other hand, continuing to subsidize fossil fuels anchors them to the economic structure, hinders the development of renewable energy, and reduces the fiscal space available to support green technologies and mitigation actions. Besides, the FiT policy needs to be designed to include provisions that prioritize smaller producers or community-based projects, and democratize energy production and distribution. If planned appropriately and coherently, FiTs can contribute to creating green jobs, thereby promoting economic growth that is compatible with environmental sustainability.

Experience so far highlights the necessity for both the public and private sectors to actively engage in fostering and advancing green finance. Central banks and regulatory authorities hold the influence to steer market dynamics towards greener practices and ensure their consistent implementation. Development banks and financial institutions play a crucial role in broadening the scope of green financial activities. State support is indispensable during the early stages of green finance, primarily through incentives and regulations. Public efforts to promote transparency and consistency in green reporting are essential; without them, monitoring green finance becomes challenging, leaving the system more susceptible to misuse. Reporting on the 'use of proceeds' is a critical component of green finance. Achieving this requires transparent disclosures from the private sector, aligned with environmental, social, and economic sustainability standards.

Environmental taxes, FiTs, and other mechanisms discussed in Section 4 play a critical role in supporting the Mediterranean region's transition to a low-carbon economy. While the EU taxonomy on sustainable finance offers a valuable reference, the region's diversity, spanning both EU and non-EU countries, calls for alignment with shared sustainability principles and taxonomies adapted to the Mediterranean context, as promoted by the updated Mediterranean Strategy for Sustainable Development (MSSD 2026-2035). Harmonization of standards would also facilitate cross-border renewable energy projects, such as exporting North African solar and wind power to Southern Europe, which remains an underexploited opportunity for the region.

These frameworks should reflect regional priorities in climate mitigation, pollution control, and ecosystem protection. Furthermore, there are social implications of any green finance measure that are discussed in the current study. These social impacts include, but are not limited to, job creation (or unemployment), energy access and affordability, social equity, public health

benefits, education and awareness. The necessity of a holistic program in financing the solutions to combat the climate crisis is clearly seen. Therefore, a macro perspective, which is not content with monetary policy and finance alone, but evaluates all the policy tools of the macro economy together, is a prerequisite for the fight against the climate crisis. In this context, it is desirable to support green finance policies and monetary tools with green fiscal policies such as fossil fuel subsidy removal, carbon tax, energy efficiency investments and incentives, tax incentives for green investments, and renewable energy investments and incentives. It is necessary to channel financial flows in a way that supports a just transition. For instance, there will be groups who will be negatively affected by subsidy removal. The finances that will be freed upon the removal of wasteful subsidies can be earmarked in order to support these disadvantaged groups.

Future research could build on these findings by expanding the scope of analysis to include the distributional and equity impacts of green finance measures, particularly in lower-income and fossil-dependent Mediterranean countries. A key area for further investigation is the extent to which environmentally harmful subsidies, such as fossil fuel subsidies, may offset or neutralize the effectiveness of green taxation and renewable energy incentives (Acar, 2024). Exploring such policy incoherencies is critical to understanding net outcomes. Additionally, empirical work could assess the dynamic effects of combining instruments (e.g., carbon pricing with green bonds or public procurement strategies), and evaluate long-term impacts on innovation, employment, and social equity. More granular, sector-specific data would also enable better targeting of green finance tools across the region. Besides, while our fixed effects framework represents a rigorous and widely accepted approach for addressing unobserved heterogeneity and common shocks in panel data, we recognize its limitations in establishing strong causal identification. In particular, fixed effects cannot fully resolve potential endogeneity concerns that might arise from policy endogeneity or reverse causality. As such, our findings should be interpreted as robust associations rather than definitive causal effects. Future research could build on this work by employing complementary strategies—such as system GMM, instrumental variables, or quasi-experimental approaches like difference-in-differences—when suitable exogenous variation becomes available.

To sum up, in Mediterranean countries, green finance tools alone may lack the necessary scope, enforcement, or complementary measures to drive significant GHG reductions. However, when coupled with stringent environmental policies and paired with coherent energy policies that do not favor fossil fuels, these tools are more likely to be applied effectively, target key sectors, and trigger systemic changes, thereby significantly decreasing emissions. Concrete regional lessons suggest: (i) increasing environmental tax revenues and strengthening the stringency of environmental policies (as reflected in higher EPS index values) in Southern and Eastern Mediterranean countries; (ii) prioritizing hydro, waste, and marine FiTs while phasing out biomass support; (iii) accelerating fossil fuel subsidy removal, especially in North Africa; and (iv) fostering cross-Mediterranean cooperation on renewable integration and sustainable finance taxonomies. This interplay underscores the importance of integrating green finance instruments within a comprehensive and coherent environmental policy framework.

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Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researchers' Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researchers' Conflict of Interest

There are no potential conflicts of interest in this study.

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APPENDIX

Table A1. Results with Lagged Independent Variables to Control for Reverse Causality

Model 1a.i: Fixed-effects, using 340 observations

Included 14 cross-sectional units

Time-series length: minimum 7, maximum 27

Dependent variable: LNGHGPC

Driscoll-Kraay standard errors, bandwidth 2

	Coefficient	Std. Error	z	p-value	
const	-4.85016	1.03627	-4.680	<0.0001	***
LNGDPPC_1	0.648141	0.0973863	6.655	<0.0001	***
REO_1	-0.00312508	0.00132005	-2.367	0.0179	**
ENV TAX_1	0.000995021	0.0138419	0.07188	0.9427	
dt_2	0.308512	0.0498327	6.191	<0.0001	***
dt_3	0.309750	0.0514360	6.022	<0.0001	***
dt_4	0.329389	0.0445898	7.387	<0.0001	***
dt_5	0.309596	0.0447315	6.921	<0.0001	***
dt_6	0.299474	0.0438286	6.833	<0.0001	***
dt_7	0.286325	0.0439159	6.520	<0.0001	***
dt_8	0.252781	0.0409915	6.167	<0.0001	***
dt_9	0.255511	0.0391831	6.521	<0.0001	***
dt_10	0.245582	0.0405402	6.058	<0.0001	***
dt_11	0.248853	0.0364703	6.823	<0.0001	***
dt_12	0.239021	0.0323418	7.390	<0.0001	***
dt_13	0.217568	0.0324023	6.715	<0.0001	***
dt_14	0.211417	0.0267609	7.900	<0.0001	***
dt_15	0.171484	0.0275122	6.233	<0.0001	***
dt_16	0.119722	0.0245236	4.882	<0.0001	***
dt_17	0.149510	0.0238144	6.278	<0.0001	***
dt_18	0.141956	0.0184980	7.674	<0.0001	***
dt_19	0.119385	0.0221821	5.382	<0.0001	***
dt_20	0.0807659	0.0220443	3.664	0.0002	***
dt_21	0.0797566	0.0154613	5.158	<0.0001	***
dt_22	0.0676104	0.0134597	5.023	<0.0001	***
dt_23	0.0407659	0.0120879	3.372	0.0007	***
dt_24	0.0614797	0.00873743	7.036	<0.0001	***
dt_25	0.00841535	0.0101187	0.8317	0.4056	
dt_26	-0.0145169	0.00341372	-4.253	<0.0001	***
dt_27	-0.0900089	0.00435822	-20.65	<0.0001	***
Mean dependent var	1.905796		S.D. dependent var	0.388619	
Sum squared resid	2.202401		S.E. of regression	0.086113	
LSDV R-squared	0.956982		Within R-squared	0.574618	
Log-likelihood	374.2585		Akaike criterion	-662.5170	
Schwarz criterion	-497.8723		Hannan-Quinn	-596.9131	
rho	0.878862		Durbin-Watson	0.269723	

Robust test for differing group intercepts -

Null hypothesis: The groups have a common intercept

est statistic: Welch F(13, 105.5) = 78.1684

with p-value = $P(F(13, 105.5) > 78.1684) = 5.91961e-48$

Table A2. Results with Lagged Independent Variables to Control for Reverse Causality

Model 1b.ii: Fixed-effects, using 175 observations

Included 8 cross-sectional units

Time-series length: minimum 21, maximum 22

Dependent variable: LNGHGPC

Driscoll-Kraay standard errors, bandwidth 2

	Coefficient	Std. Error	z	p-value	
const	-5.61298	0.507608	-11.06	<0.0001	***
LNGDPPC_1	0.611586	0.0582633	10.50	<0.0001	***
FOSSIL_1	0.0153694	0.00227852	6.745	<0.0001	***
ENV TAX_1	-0.0116666	0.00800425	-1.458	0.1450	
EPS	-0.0127776	0.0183685	-0.6956	0.4867	
EPSxENV TAX	0.00736324	0.00368507	1.998	0.0457	**
dt_2	0.185632	0.0333864	5.560	<0.0001	***
dt_3	0.173573	0.0325016	5.340	<0.0001	***
dt_4	0.184289	0.0306581	6.011	<0.0001	***
dt_5	0.174832	0.0292114	5.985	<0.0001	***
dt_6	0.165875	0.0285438	5.811	<0.0001	***
dt_7	0.166540	0.0268465	6.203	<0.0001	***
dt_8	0.140782	0.0239959	5.867	<0.0001	***
dt_9	0.156881	0.0231603	6.774	<0.0001	***
dt_10	0.148283	0.0217435	6.820	<0.0001	***
dt_11	0.154110	0.0189991	8.111	<0.0001	***
dt_12	0.134345	0.0164992	8.142	<0.0001	***
dt_13	0.108286	0.0156208	6.932	<0.0001	***
dt_14	0.102083	0.0137630	7.417	<0.0001	***
dt_15	0.0574731	0.0130517	4.404	<0.0001	***
dt_16	0.00358196	0.0127176	0.2817	0.7782	
dt_17	0.0369049	0.0118537	3.113	0.0018	***
dt_18	0.0345650	0.00904975	3.819	0.0001	***
dt_19	0.0260393	0.00795416	3.274	0.0011	***
dt_20	-0.00581244	0.00701280	-0.8288	0.4072	
dt_21	-0.0118427	0.00327409	-3.617	0.0003	***
dt_22	0.0273996	0.00173608	15.78	<0.0001	***
Mean dependent var	2.100198		S.D. dependent var	0.228692	
Sum squared resid	0.272226		S.E. of regression	0.043940	
LSDV R-squared	0.970086		Within R-squared	0.849982	
Log-likelihood	317.4526		Akaike criterion	-566.9053	
Schwarz criterion	-459.3025		Hannan-Quinn	-523.2585	
rho	0.516854		Durbin-Watson	0.911586	
Robust test for differing group intercepts -					
Null hypothesis: The groups have a common intercept					
Test statistic: Welch F(7, 71.1) = 192.715					
with p-value = P(F(7, 71.1) > 192.715) = 1.38018e-43					

Table A3. Results with Lagged Independent Variables to Control for Reverse Causality

Model 2a.i: Fixed-effects, using 340 observations

Included 14 cross-sectional units

Time-series length: minimum 7, maximum 27

Dependent variable: LNGHGPC

Driscoll-Kraay standard errors, bandwidth 2

	Coefficient	Std. Error	z	p-value	
const	−4.96675	1.06796	−4.651	<0.0001	***
LNGDPPC_1	0.655059	0.0996257	6.575	<0.0001	***
REO_1	−0.00289276	0.00140209	−2.063	0.0391	**
CLIMTAX_1	0.00898503	0.0121977	0.7366	0.4614	
dt_2	0.340095	0.0517530	6.572	<0.0001	***
dt_3	0.336426	0.0536665	6.269	<0.0001	***
dt_4	0.354648	0.0461467	7.685	<0.0001	***
dt_5	0.334964	0.0466739	7.177	<0.0001	***
dt_6	0.324429	0.0452864	7.164	<0.0001	***
dt_7	0.311989	0.0453846	6.874	<0.0001	***
dt_8	0.280419	0.0430449	6.515	<0.0001	***
dt_9	0.282260	0.0411084	6.866	<0.0001	***
dt_10	0.271945	0.0424603	6.405	<0.0001	***
dt_11	0.274160	0.0380182	7.211	<0.0001	***
dt_12	0.264302	0.0338740	7.802	<0.0001	***
dt_13	0.243354	0.0340628	7.144	<0.0001	***
dt_14	0.237355	0.0284398	8.346	<0.0001	***
dt_15	0.197036	0.0293492	6.714	<0.0001	***
dt_16	0.145663	0.0263946	5.519	<0.0001	***
dt_17	0.173862	0.0255069	6.816	<0.0001	***
dt_18	0.163767	0.0201271	8.137	<0.0001	***
dt_19	0.142489	0.0237905	5.989	<0.0001	***
dt_20	0.103497	0.0236779	4.371	<0.0001	***
dt_21	0.100245	0.0163711	6.123	<0.0001	***
dt_22	0.0876516	0.0140966	6.218	<0.0001	***
dt_23	0.0603985	0.0135044	4.472	<0.0001	***
dt_24	0.0802961	0.00985703	8.146	<0.0001	***
dt_25	0.0279384	0.0112848	2.476	0.0133	**
dt_26	0.00450957	0.00424428	1.063	0.2880	
dt_27	−0.0706289	0.00408288	−17.30	<0.0001	***
Mean dependent var	1.908262	S.D. dependent var		0.386402	
Sum squared resid	2.138419	S.E. of regression		0.084853	
LSDV R-squared	0.957751	Within R-squared		0.584511	
Log-likelihood	379.2703	Akaike criterion		−672.5406	
Schwarz criterion	−507.8960	Hannan-Quinn		−606.9367	
rho	0.875734	Durbin-Watson		0.274043	

Joint test on named regressors -

Test statistic: $F(3, 26) = 74.3967$

with p-value = $P(F(3, 26) > 74.3967) = 6.90656e-13$

Robust test for differing group intercepts -

Null hypothesis: The groups have a common intercept

Test statistic: Welch $F(13, 106.0) = 78.1179$

with p-value = $P(F(13, 106.0) > 78.1179) = 4.30059e-48$

Table A4. Results with Lagged Independent Variables to Control for Reverse Causality

Model 2b.ii: Fixed-effects, using 176 observations

Included 8 cross-sectional units

Time-series length = 22

Dependent variable: LNGHGPC

Driscoll-Kraay standard errors, bandwidth 2

	Coefficient	Std. Error	z	p-value	
const	-5.66794	0.558416	-10.15	<0.0001	***
LNGDPPC_1	0.617714	0.0629746	9.809	<0.0001	***
FOSSIL_1	0.0150990	0.00225822	6.686	<0.0001	***
CLIMTAX_1	-0.0109749	0.00911326	-1.204	0.2285	
EPS	-0.0238152	0.0119267	-1.997	0.0458	**
EPSxCLIMTAX	0.0125143	0.00247545	5.055	<0.0001	***
dt_2	0.196854	0.0305365	6.447	<0.0001	***
dt_3	0.181696	0.0299400	6.069	<0.0001	***
dt_4	0.191491	0.0280176	6.835	<0.0001	***
dt_5	0.182390	0.0265565	6.868	<0.0001	***
dt_6	0.172934	0.0257355	6.720	<0.0001	***
dt_7	0.175079	0.0249926	7.005	<0.0001	***
dt_8	0.148849	0.0222588	6.687	<0.0001	***
dt_9	0.164925	0.0213978	7.708	<0.0001	***
dt_10	0.156461	0.0203336	7.695	<0.0001	***
dt_11	0.164021	0.0181497	9.037	<0.0001	***
dt_12	0.145041	0.0164344	8.825	<0.0001	***
dt_13	0.119217	0.0161645	7.375	<0.0001	***
dt_14	0.110780	0.0143901	7.698	<0.0001	***
dt_15	0.0677945	0.0132385	5.121	<0.0001	***
dt_16	0.0127151	0.0129515	0.9817	0.3262	
dt_17	0.0433177	0.0124104	3.490	0.0005	***
dt_18	0.0404892	0.00898774	4.505	<0.0001	***
dt_19	0.0311951	0.00817294	3.817	0.0001	***
dt_20	-0.00236661	0.00739222	-0.3201	0.7489	
dt_21	-0.00972173	0.00353763	-2.748	0.0060	***
dt_22	0.0278587	0.00158301	17.60	<0.0001	***
Mean dependent var	2.099509	S.D. dependent var		0.228221	
Sum squared resid	0.259400	S.E. of regression		0.042741	
LSDV R-squared	0.971541	Within R-squared		0.857064	
Log-likelihood	324.0152	Akaike criterion		-580.0305	
Schwarz criterion	-472.2340	Hannan-Quinn		-536.3088	
rho	0.489893	Durbin-Watson		0.964457	

Joint test on named regressors -

Test statistic: $F(5, 21) = 194.601$

with p-value = $P(F(5, 21) > 194.601) = 7.57204e-17$

Robust test for differing group intercepts -

Null hypothesis: The groups have a common intercept

Test statistic: Welch $F(7, 71.5) = 154.961$

with p-value = $P(F(7, 71.5) > 154.961) = 1.36125e-40$

SUSTAINABILITY PERFORMANCE EVALUATION MODEL OF BANKING SECTOR: AN INTUITIONISTIC FUZZY MULTI-CRITERIA APPROACH WITH A NON-HOMOGENEOUS DATA SET*

Bankacılık Sektörü Sürdürülebilirlik Performans Değerlendirme Modeli: Homojen Olmayan Veri Seti ile Sezgisel Bulanık Çok Kriterli Yaklaşım

Burcu SIMSEK YAGLI & Nuri Ozgur DOGAN*****

Abstract

This study aims to develop a comprehensive and multidimensional framework to assess sustainability performance in the banking sector. We propose the Banking Sector Sustainability Model (BSSM), which integrates six dimensions: social, innovation, governance, environmental, economic, and financial criteria. To determine the relative importance of these dimensions, the study employs the Interval-Valued Intuitionistic Fuzzy Best-Worst Method (IVIF-BWM). Then, banks are ranked using the Intuitionistic Fuzzy Weighted Correlation Coefficient (IF-WCC) method, allowing for comparison based on diverse and heterogeneous data. The results reveal that expert groups have different priorities, with some highlighting environmental concerns and others prioritizing economic factors, indicating the framework's potential to capture diverse stakeholder perspectives. Sensitivity analyses confirm the stability and reliability of the proposed approach. Overall, the study proposes novel and practical tool for evaluating sustainability in the banking sector. The framework can support decision-makers, financial institutions, and researchers in promoting sustainable banking and enhancing transparency and accountability in the sector.

Keywords:

Banking Sector Sustainability Model, Intuitionistic Fuzzy Sets, BWM, WCC, Heterogeneous Data.

JEL Codes:

G21, Q01, D81, C44.

Öz

Bu çalışma, bankacılık sektöründe sürdürülebilirlik performansını değerlendirmek için kapsamlı ve çok boyutlu bir çerçeve geliřtirmeyi amaçlamaktadır. Çalışmada, sosyal, inovasyon, yönetim, çevresel, ekonomik ve finansal kriterler olmak üzere altı boyutu birleřtiren Bankacılık Sektörü Sürdürülebilirlik Modeli (BSSM) önerilmektedir. Bu boyutların göreceli önemini belirlemek için Aralık Değerli Sezgisel Bulanık Best Worst Metodu (IVIF-BWM) kullanılmaktadır. Ardından, bankalar heterojen verilere dayalı karřılařtırmaya olanak tanıyan Sezgisel Bulanık Ağırlıklı Korelasyon Katsayısı (IF-WCC) yöntemi kullanılarak sıralanmaktadır. Sonuçlar, uzman grupları arasında önceliklerde farklılıklar olduğunu göstermektedir; bazıları çevresel kaygıları vurgularken diğersleri ekonomik faktörleri önceliklendirmektedir ve bu da çerçevenin farklı paydař bakış açılarını yakalama yeteneğini göstermektedir. Duyarlılık analizleri, önerilen yaklaşımın istikrarını ve güvenilirliğini doğrulamaktadır. Özetle çalışma, bankacılık sektöründe sürdürülebilirliği değerlendirmek için yeni ve pratik bir araç sağlamaktadır. Çerçevenin karar vericileri, finans kuruluşlarını ve arařtırmacıları sürdürülebilir bankacılığa teřvik etmede ve sektörde řeffaflık ve hesap verebilirliği artırmada etkili olacağına inanılmaktadır.

Anahtar

Kelimeler:

Bankacılık Sektörü Sürdürülebilirlik Modeli, Sezgisel Bulanık Kümeler, BWM, WCC, Heterojen Veri.

JEL Kodları:

G21, Q01, D81, C44.

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1. Introduction

Contemporary global challenges such as climate change, the depletion of natural resources, social inequalities, and economic vulnerabilities have made sustainability an essential framework for both individuals and organizations that seeking to ensure long-term resilience and well-being. According to the Global Risks Report 2024, the most significant risks anticipated over the next decade are environmental in nature, including extreme weather events, biodiversity loss, and natural resource scarcity (World Economic Forum, 2024). This alarming outlook compels all sectors to adopt a more proactive approach toward achieving the Sustainable Development Goals (SDGs). Furthermore, growing environmental awareness, rapid technological advancements, evolving regulatory requirements, and changing consumer preferences toward eco-conscious practices increasingly necessitate the integration of sustainability-oriented strategies across both manufacturing and service industries (Barbosa and de Oliveira, 2021). In this context, the development of environmentally friendly products and services, the implementation of waste recycling programs, corporate social responsibility (CSR) initiatives, and the efficient use of resources have emerged as strategic priorities for businesses.

The growing environmental and social risks at the global level have significantly increased the sensitivity of the financial sector particularly banking toward sustainability concerns. Given its capacity to allocate financial resources, the banking sector holds a pivotal role in driving the sustainability transformation. According to the United Nations Environment Programme Finance Initiative (UNEP FI), as of 2024, more than 300 banks representing over 50% of global banking assets have committed to the Principles for Responsible Banking (UNEP FI, 2024). On a national scale, data from the Banks Association of Türkiye (TBB) show that, as of 2023, 25 out of 60 banks operating in the Turkish banking sector publish sustainability reports, while 15 explicitly declare their contributions to the SDGs (TBB, 2023).

Sustainability practices have become increasingly important in sectors such as banking, which are deeply interconnected with other industries and thus have broad systemic impacts. Sustainable banking encompasses a wide array of practices, including the implementation of environmental policies, transparency with stakeholders, and collaboration with governments and non-governmental organizations to promote sustainability (Bouma et al., 2017). Rather than being limited to economic performance alone, sustainability is understood as a holistic approach that simultaneously considers environmental, economic, and social dimensions (Kumar et al., 2018). Based on Stakeholder Theory and the Triple Bottom Line (TBL) framework, it would be appropriate to add overarching dimensions to the assessment of bank sustainability. In many cases, this approach is framed within the Environmental, Social, and Governance (ESG) model, which emphasizes the need for multi-dimensional performance evaluation to ensure the continuity and effectiveness of systems and processes (Zhou et al., 2018). Despite this growing importance, some banks are observed to adopt sustainability initiatives only in a limited manner due to concerns over costs or fail to communicate these efforts transparently to the public (Rabea'Hadi et al., 2023). Additionally, significant inconsistencies exist in the content of information disclosed through bank websites, integrated reports, and sustainability reports (TBB, 2023), making it difficult to comparatively assess the sustainability performance of banks.

When discussing sustainability in the banking industry, the studies in the literature generally focus on the CSR (Nájera-Sánchez, 2020). Furthermore, a review of recent studies on performance evaluation in the banking sector which has made significant strides toward

sustainability, reveals that the focus is predominantly on the relationship between CSR and financial performance (FP). However, comprehensive models that address the multidimensional nature of sustainability performance remain limited (see Karagiorgos, 2010; Ahmed et al., 2012; Pour et al., 2014; Kılıç et al., 2015; Ashraf et al., 2017; Weber, 2017; Wang et al., 2018; Gangi et al., 2018; Nizam, 2019; Khattak, 2021; Pala, 2022). Studies analyzing the CSR-FP relationship in the banking sector typically employ regression analysis, statistical techniques, or content analysis (Chowdhury and Paul, 2020). The findings suggest that the impact of CSR on FP can be positive, negative, or neutral (Islam et al., 2012). Nonetheless, evaluating banks' sustainability activities solely through financial metrics is insufficient.

Various institutions and organizations have developed diverse models for evaluating sustainability performance. Research in this field extends beyond practice-oriented entities and is extensively addressed within the academic literature. Specifically, performance evaluation models that capture the multidimensional nature of sustainability have been proposed. These models often employ multi-criteria decision-making (MCDM) methods and a range of quantitative analysis techniques to assign weights to performance criteria and rank alternatives such as banks. Notable studies in this area include Hassan and Harrahap (2010), Ohene-Asare and Asmild (2012), Özçelik and Öztürk (2014), Aras et al. (2016, 2017, 2018), Akin and Yılmaz (2016), Rebai et al. (2016), Raut et al. (2017), Korzeb and Samaniego-Medina (2019), Stauropoulou and Sardanou (2019), Simsek Yagli et al. (2022), Ecer and Pamucar (2022), Nepomuceno et al. (2024), and Sharma and Kumar (2024). However, challenges related to limited data availability and insufficient transparency in some banks' sustainability disclosures hinder the accuracy and comparability of performance analyses. In this context, intuitionistic fuzzy logic-based MCDM methods have gained importance as they effectively handle linguistic and uncertain data. As a systematic approach to analyzing complex, multidimensional decision problems, MCDM proves particularly useful for addressing sustainability evaluation.

Additionally, Aracil et al. (2021) emphasize that sustainability evaluations in the banking sector often focus on specific aspects and lack a comprehensive, multidimensional assessment. Therefore, there is a clear need for a methodological framework that offers a practical and comprehensible solution by integrating multiple dimensions to evaluate sustainability performance in banking. Current literature addressing this need remains limited. Moreover, evaluation outcomes can vary significantly depending on different stakeholder perspectives, highlighting the importance of examining and comparing the views of diverse groups to promote a sustainable banking sector (Nájera-Sánchez, 2020). Addressing these identified gaps, this study aims to propose an intuitionistic fuzzy set-based, multi-criteria, and practical methodological framework for assessing sustainability performance in the banking sector. Within this scope, a Banking Sector Sustainability Model (BSSM) is first developed; subsequently, the criteria weights are determined using the Interval-Valued Intuitionistic Fuzzy Best-Worst Method (IVIF-BWM), and banks are ranked via the Weighted Correlation Coefficient (WCC) method. This approach facilitates a multidimensional and comparative evaluation mechanism tailored specifically to the banking sector. The current study seeks to achieve the following research objectives: (i) identifying the key sustainability dimensions relevant to the banking sector, (ii) determining their relative importance through expert evaluations, and comparing the results and (iii) applying the proposed multi-criteria approach to derive a robust and comparable ranking of banks. This research therefore bridges the gap between theoretical sustainability concepts and their practical operationalization within the sustainability of banking sector.

2. Banking Sector Sustainability Model (BSSM)

Ehrenfeld (2008) emphasized that sustainability should not merely be managed, but also systematically measured and evaluated. For businesses to operate sustainably, it is crucial to implement an effective performance measurement system capable of assessing sustainability outcomes. In this context, organizations increasingly seek models that facilitate objective, user-friendly evaluation and enable benchmarking against competitors.

The theoretical foundation of the proposed BSSM is grounded mainly in Stakeholder Theory (Freeman and McVea, 2005) and the TBL framework (Elkington, 1997), which emphasize that sustainable performance cannot be captured solely through financial metrics. In the banking sector, sustainability emerges as a multidimensional construct encompassing economic, social, and environmental responsibilities toward diverse stakeholders. Although the three dimensions of the TBL approach appear to align with stakeholder theory, they do not fully address the varying expectations of stakeholders. Therefore, a more comprehensive framework based on relevant theories is required.

Existing sustainability frameworks such as the TBL, Global Reporting Initiative (GRI), Dow Jones Sustainability Index (DJSI), and the ESG criteria typically address economic, social, and environmental dimensions and serve as foundational tools for sector or region-specific performance assessments. However, these models alone are often insufficient for conducting comprehensive evaluations at the sectoral or regional level. For instance, while GRI primarily functions as a reporting standard rather than a performance evaluation tool, TBL, despite its widespread acceptance, requires customization to reflect sector-specific dynamics. Similarly, other frameworks necessitate adaptation to the contextual needs of particular industries.

Recent studies highlight an increasing emphasis on environmental aspects in sustainability performance assessments, alongside the integrated evaluation of economic, social, and environmental pillars (Morioka and de Carvalho, 2016). However, significant challenges remain in managing, measuring, and reporting sustainability comprehensively and consistently (Aras et al., 2018). Traditional frameworks such as TBL, GRI, DJSI, and ESG provide a foundation but often fall short in capturing sector-specific complexities, particularly in banking. Financial institutions, especially banks, play a critical role in sustainable development, and growing stakeholder pressure necessitates more robust, transparent, and objective sustainability performance models (Stauropoulou and Sardianou, 2019). To address contemporary challenges such as digital transformation and governance transparency, the BSSM extends the classical TBL framework by incorporating innovation, governance, and financial dimensions, aligning with the principles of Institutional Theory (DiMaggio and Powell, 1983) and the Dynamic Capabilities perspective (Teece, 2018). Thus, the dimensions reflect both normative expectations and strategic capabilities that jointly determine sustainable banking performance. In response to these gaps, this study introduces the BSSM that is a novel decision support tool developed through literature review and expert consultation (Figure 1).

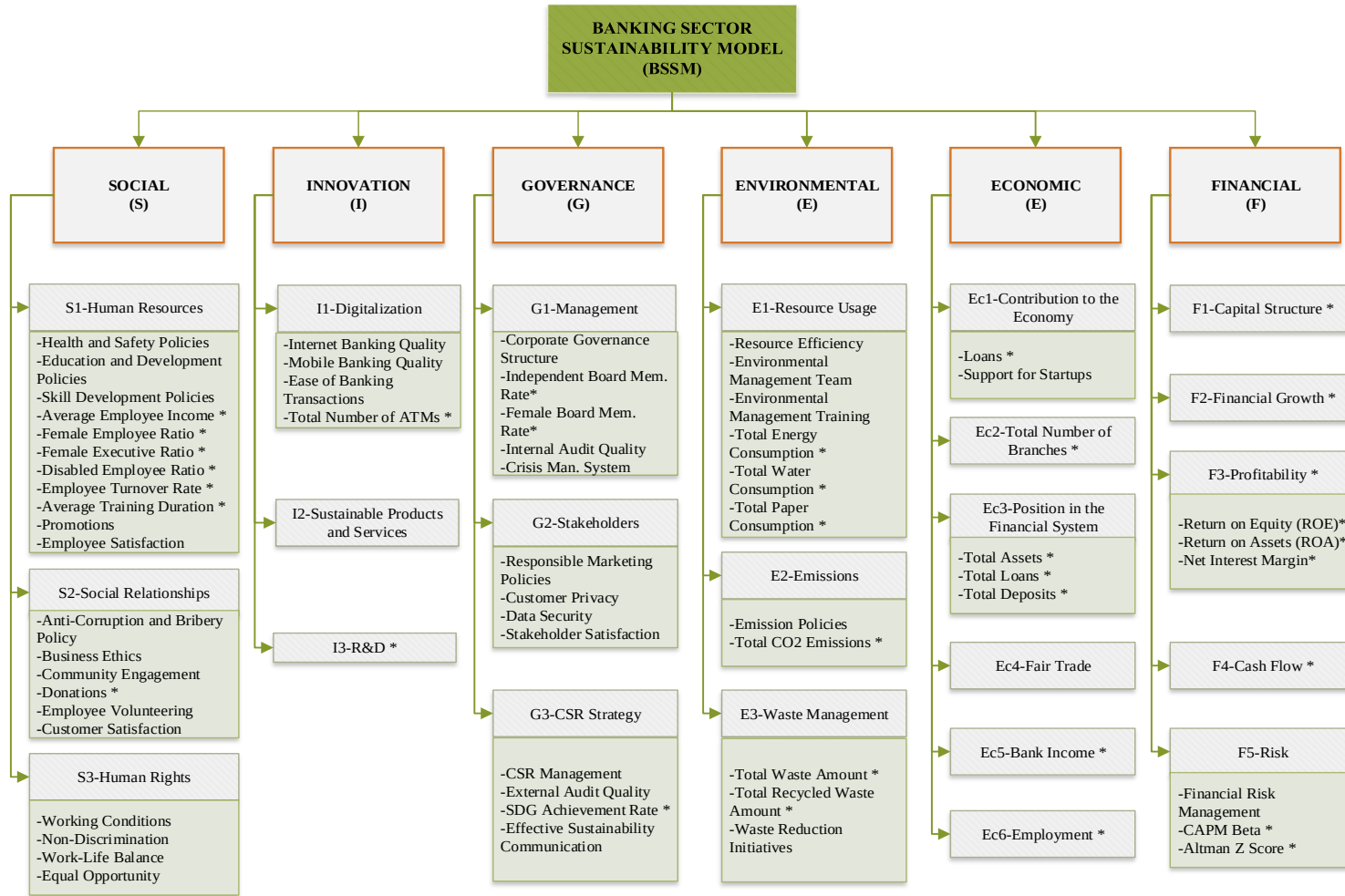


Figure 1. Banking Sector Sustainability Model (BSSM)

While drawing on established frameworks (TBL, GRI, ESG, DJSI, BIST Sustainability Index, UN SDGs, and ISO 26000), the BSSM extends beyond existing models in several ways. First, it incorporates Innovation as a sixth core dimension, alongside Social, Environmental, Governance, Economic, and Financial, reflecting the growing relevance of digitalization in banking. It reflects the sector's adaptive capacity and long-term competitiveness. Second, it integrates both qualitative and quantitative data types, increasing flexibility and real-world applicability. Unlike many existing models based on homogeneous data sets, BSSM incorporates both quantitative data (interval or crisp values) and qualitative data, denoted by an asterisk (*) in Figure 1. Third, it is structured as a multi-criteria, multi-level model (SIGEEF), comprising 6 main criteria, 23 sub-criteria, and 60 third-level indicators, all tailored specifically for the banking sector. In summary, the theoretical structure of the BSSM integrates normative principles (Stakeholder theory and TBL frameworks) with institutional and strategic perspectives (Institutional and Dynamic Capabilities theories). Therefore, the BSSM offers a comprehensive, adaptable, and stakeholder-friendly framework for evaluating sustainability performance. Its development is rooted in both academic foundations and practical relevance, and as detailed in Appendix 1, it uniquely synthesizes and contextualizes a wide range of global and national standards.

3. Methodology

To address the study's research objectives, a structured methodological framework was developed based on the BSSM model, incorporating both primary and secondary data. Given the model's multidimensional nature, MCDM techniques were employed. To account for the uncertainty and subjectivity inherent in expert evaluations, intuitionistic fuzzy sets were utilized. The BWM was applied to determine the weights of the criteria, while the WCC method was used to rank the banks according to their sustainability performance. The following sections provide a detailed explanation of each methodological steps.

3.1. Multi-Criteria Decision Making

Decision-making is a fundamental aspect of both individual and organizational life. Real-world problems often involve multiple data types, ranging from precise and objective to subjective and uncertain (Belton and Stewart, 2002). As most decision problems are inherently multi-criteria in nature, MCDM provides an effective framework for analyzing complex issues and achieving balanced, optimal solutions (Amor et al., 2020). As a result, MCDM has become a prominent research area within decision theory (Mi et al., 2019).

MCDM methods offer structured approaches for evaluating complex decisions by helping decision-makers compare alternatives across various criteria (Wang et al., 2017). These techniques support holistic analyses and informed choices without neglecting critical details (Carayannis et al., 2018). A wide range of MCDM methods has been developed for tasks such as criteria weighting, prioritization, and alternative ranking. However, no single, universally accepted MCDM methodology exists, as methods differ in assumptions, complexity, and computational procedures. A common criticism is that different MCDM techniques can produce varying results for the same problem (El Amine et al., 2014). Thus, selecting the most appropriate

method requires a clear understanding of their respective strengths and limitations (Çelikkbilek and Tüysüz, 2020).

Since the 1950s, MCDM has been widely applied in both managerial practice and academic research. Its key application areas include corporate sustainability (Chowdhury and Paul, 2020), financial performance (Abdel-Basset et al., 2020), logistics (Chejarla et al., 2022), human resources (Esangbedo et al., 2021), energy policy (Kaya et al., 2018), location selection (Shao et al., 2020), and tourism (Vatankhah et al., 2023).

3.2. Interval Valued Intuitionistic Fuzzy Sets

Intuitionistic fuzzy sets (IFSs) consider membership and non-membership functions along with hesitation degrees. However, interval-valued intuitionistic fuzzy sets (IVIFSs) advance beyond IFSs by handling membership and non-membership functions as intervals, making them more effective in managing uncertainty. This provides advantages in modeling and solving more complex problems. The fundamental definitions of IVIFSs are introduced in the studies by Onar et al. (2015) and Karařan et al. (2020).

3.3. IVIF Best Worst Method

The BWM was first developed by Rezaei (2015). It is a recent technique that excels in reducing the number of pairwise comparisons while maintaining consistency among judgments. Unlike other weighting methods, BWM requires comparisons only between the best (most important or most desired) criterion and all other criteria, as well as between all criteria and the worst (least important or least desired) criterion. Compared to other methods, BWM is simpler, more accurate, and eliminates unnecessary (redundant) comparisons (Pamućar et al., 2020). The method aims to determine optimal weights and ensure the consistency of matrices through a simple optimization model constructed from the comparison process (Rezaei et al., 2016).

The five steps of the IVIF-BWM algorithm are listed below (Wang et al., 2021; Mohammadi et al., 2022; Simsek Yagli et al., 2022):

Step 1. From the decision-makers' perspective, the most important (or best - C_B) criterion and the least important (or worst - C_W) criterion are identified from a predefined set of criteria ($C_j, j=1,2,...,n$).

Step 2. Using a linguistic scale, the most important criterion is compared to all other criteria by each decision-maker (DM_k) (Best-to-Others vector).

$$\tilde{R}_B^{(k)} = (\tilde{r}_{B1}^{(k)}, \tilde{r}_{B2}^{(k)}, \dots, \tilde{r}_{Bn}^{(k)}) \quad (1)$$

Here, $\tilde{r}_{Bj}^{(k)} = ([\tilde{\mu}_{Bj}^{(L)}, \tilde{\mu}_{Bj}^{(U)}], [\tilde{\nu}_{Bj}^{(L)}, \tilde{\nu}_{Bj}^{(U)}])$ represents the IVIF preference of the most important criterion (C_B) over the other criteria C_j as expressed by each decision-maker DM_k .

Step 3. Using a linguistic scale, each k th decision-maker (DM_k) compares the other criteria to the least important criterion (C_W), forming the Others-to-Worst vector.

$$\tilde{R}_W^{(k)} = (\tilde{r}_{1W}^{(k)}, \tilde{r}_{2W}^{(k)}, \dots, \tilde{r}_{nW}^{(k)}) \quad (2)$$

Here, $\tilde{r}_{jW}^{(k)} = \left(\left[\tilde{\mu}_{jW}^{(L)}, \tilde{\mu}_{jW}^{(U)} \right], \left[\tilde{\nu}_{jW}^{(L)}, \tilde{\nu}_{jW}^{(U)} \right] \right)$ represents the IVIF preference of each criterion C_j relative to the least important criterion (C_W), as expressed by each decision-maker DM_k .

Step 4. The optimal weights are calculated for each decision-maker DM_k .

Here, it is assumed that: $\tilde{\omega}_B^{(k)} = \left(\left[\tilde{\mu}_B^{(L)}, \tilde{\mu}_B^{(U)} \right], \left[\tilde{\nu}_B^{(L)}, \tilde{\nu}_B^{(U)} \right] \right)$, $\tilde{\omega}_W^{(k)} = \left(\left[\tilde{\mu}_W^{(L)}, \tilde{\mu}_W^{(U)} \right], \left[\tilde{\nu}_W^{(L)}, \tilde{\nu}_W^{(U)} \right] \right)$ and $\tilde{\omega}_j^{(k)} = \left(\left[\tilde{\mu}_j^{(L)}, \tilde{\mu}_j^{(U)} \right], \left[\tilde{\nu}_j^{(L)}, \tilde{\nu}_j^{(U)} \right] \right)$ represent the IVIF weights of the best, worst, and j th criteria, respectively, as determined by decision maker DM_k . The optimal weight for each criterion is derived based on minimizing the maximum absolute deviations between the calculated ratios and the corresponding IVIF preferences: $\left| \frac{\tilde{\omega}_B^{(k)}}{\tilde{\omega}_j^{(k)}} - \tilde{r}_{Bj}^{(k)} \right|$ and $\left| \frac{\tilde{\omega}_j^{(k)}}{\tilde{\omega}_W^{(k)}} - \tilde{r}_{jW}^{(k)} \right|$. A solution is then obtained that minimizes these maximum absolute deviations for

all criteria C_j , ensuring that the optimal weights satisfy the preferences provided by the decision maker. Additionally, taking into account that the weights must be non-negative and their sum must equal to 1, the following optimization model (Model 1) is solved to obtain the optimal criterion weights for each decision maker DM_k . Model 1:

min ε

St.

$$\begin{aligned} & \left| \mu_B^{L(k)} + \nu_j^{L(k)} - \mu_B^{L(k)} \cdot \nu_j^{L(k)} - \mu_{Bj}^{L(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \mu_B^{U(k)} + \nu_j^{U(k)} - \mu_B^{U(k)} \cdot \nu_j^{U(k)} - \mu_{Bj}^{U(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \nu_B^{L(k)} + \mu_j^{L(k)} - \nu_B^{L(k)} \cdot \mu_j^{L(k)} - \nu_{Bj}^{L(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \nu_B^{U(k)} + \mu_j^{U(k)} - \nu_B^{U(k)} \cdot \mu_j^{U(k)} - \nu_{Bj}^{U(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \mu_j^{L(k)} + \nu_W^{L(k)} - \mu_j^{L(k)} \cdot \nu_W^{L(k)} - \mu_{jW}^{L(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \mu_j^{U(k)} + \nu_W^{U(k)} - \mu_j^{U(k)} \cdot \nu_W^{U(k)} - \mu_{jW}^{U(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \nu_j^{L(k)} + \mu_W^{L(k)} - \nu_j^{L(k)} \cdot \mu_W^{L(k)} - \nu_{jW}^{L(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \left| \nu_j^{U(k)} + \mu_W^{U(k)} - \nu_j^{U(k)} \cdot \mu_W^{U(k)} - \nu_{jW}^{U(k)} \right| \leq \varepsilon, \text{ for all } C_j \text{ criteria} \\ & \sum_{j=1}^n S(\tilde{\omega}_j^{(k)}) = 1 \\ & S(\tilde{\omega}_j^{(k)}) \geq 0, \text{ for all } C_j \text{ criteria} \end{aligned}$$

By solving Model 1 above, the optimal weights of each criterion for decision maker DM_k , denoted as ε^* and $\tilde{\omega}^{(k)} = (\tilde{\omega}_1, \tilde{\omega}_2, \dots, \tilde{\omega}_n)^{(k)}$ are obtained. Here, ε^* is defined as the consistency ratio of the comparison system, and a value close to zero indicates that the comparisons made by DM_k are highly consistent (Rezaei et al., 2016).

Step 5. Each criterion's optimal weight is defuzzified. Given that $\tilde{\omega}_j = ([a, b], [c, d])$

$$\omega_j = \frac{a + a(1 - a - c) + b + b(1 - b - d)}{2} \quad (3)$$

3.4. Weighted Correlation Coefficient

Numerous MCDM methods have been developed to evaluate and rank alternatives based on predefined criteria. In this study, the WCC method proposed by Ye (2010) is employed. This

approach ranks alternatives by calculating the weighted correlation between each alternative and an ideal solution, thereby facilitating the identification of the most suitable option.

Let $X = \{x_1, x_2, \dots, x_n\}$ be a finite universe, and consider $A = \{ \langle x_i, \mu_A(x_i), \nu_A(x_i) \rangle \mid x_i \in X \}$ and $B = \{ \langle x_i, \mu_B(x_i), \nu_B(x_i) \rangle \mid x_i \in X \}$ as two intuitionistic fuzzy numbers (IFNs). The correlation coefficient between A and B is given by Equation 4 (Gerstenkorn and Mańko, 1991).

$$k(A, B) = \frac{C(A, B)}{\sqrt{T(A) \cdot T(B)}} \quad (4)$$

Here, $(A, B) = \sum_{i=1}^n (\mu_A(x_i) \mu_B(x_i) + \nu_A(x_i) \nu_B(x_i))$, $T(A) = \sum_{i=1}^n (\mu_A^2(x_i) + \nu_A^2(x_i))$ and $T(B) = \sum_{i=1}^n (\mu_B^2(x_i) + \nu_B^2(x_i))$.

The correlation coefficient between two intuitionistic fuzzy sets (IFS) A and B should satisfy the following properties (Ye, 2010): (i) $0 \leq k(A, B) \leq 1$, (ii) $k(A, B) = k(B, A)$, (iii) $k(A, B) = 1$ if and only if $A = B$. Then, the obtained criterion weights ($w_j = w_1, w_2, \dots, w_n$) are used in the formula in Equation 5 to calculate the WCC between alternative A_i and the ideal alternative A^* .

$$W_i(A^*, A_i) = \frac{C_i(A^*, A_i)}{\sqrt{T^*(A^*) \cdot T_i(A_i)}} = \frac{\sum_{j=1}^n w_j \mu_{A_i}(C_j)}{\sqrt{\sum_{j=1}^n w_j (\mu_{A_i}^2(C_j) + \nu_{A_i}^2(C_j))}} \quad (5)$$

The larger the value of the weighted correlation coefficient W_i , the closer the alternative A_i is to the ideal alternative A^* , and therefore, the better the alternative A_i is. Consequently, all alternatives can be ranked according to their weighted correlation coefficients, allowing the best alternative to be selected.

The weighted correlation coefficient W_i between A^* and A_i (for $i=1, 2, \dots, m$) should satisfy the following properties: (i) $0 \leq W_i(A^*, A_i) \leq 1$, (ii) $W_i(A^*, A_i) = W_i(A_i, A^*)$, (iii) $W_i(A^*, A_i) = 1$ if and only if $A^* = A_i$.

4. Applications and Findings

Undoubtedly, each sector has its own sustainability priorities, necessitating sector-specific and applicable evaluation models. To address the absence of such a framework in the banking sector, this study proposes the BSSM, designed to assess sustainability performance using both qualitative and quantitative data tailored to the banking context. Expert feedback confirmed the model's suitability while also emphasizing that not all criteria carry equal importance. Therefore, MCDM techniques were employed to assign weights reflecting the relative significance of each criterion.

The overall research framework, which illustrates the research objectives in detail, is outlined in Figure 2. Given the hierarchical and multidimensional structure of BSSM, traditional MCDM methods may fall short in addressing the uncertainty in expert judgments. To overcome this, the study integrates IVIF sets with the BWM, a practical and efficient weighting approach that accommodates imprecise expert evaluations (Büyüközkan et al., 2020). The aim is to enable experts to determine the relative importance of BSSM criteria, thereby guiding bank managers in resource allocation and enhancing strategic decision-making. This approach contributes a novel

methodological framework to the sustainability performance literature. Due to the difficulty in accessing comprehensive data for all 60 sub-criteria, four banks were selected and anonymized as Bank 1 through Bank 4. After expert validation of BSSM, the WCC method was adopted to rank banks based on sustainability performance. The WCC method is particularly suitable for handling heterogeneous data structures (Cavallaro et al., 2018). The final stage involved data collection to implement the weighting and ranking procedures in line with the study's objectives.

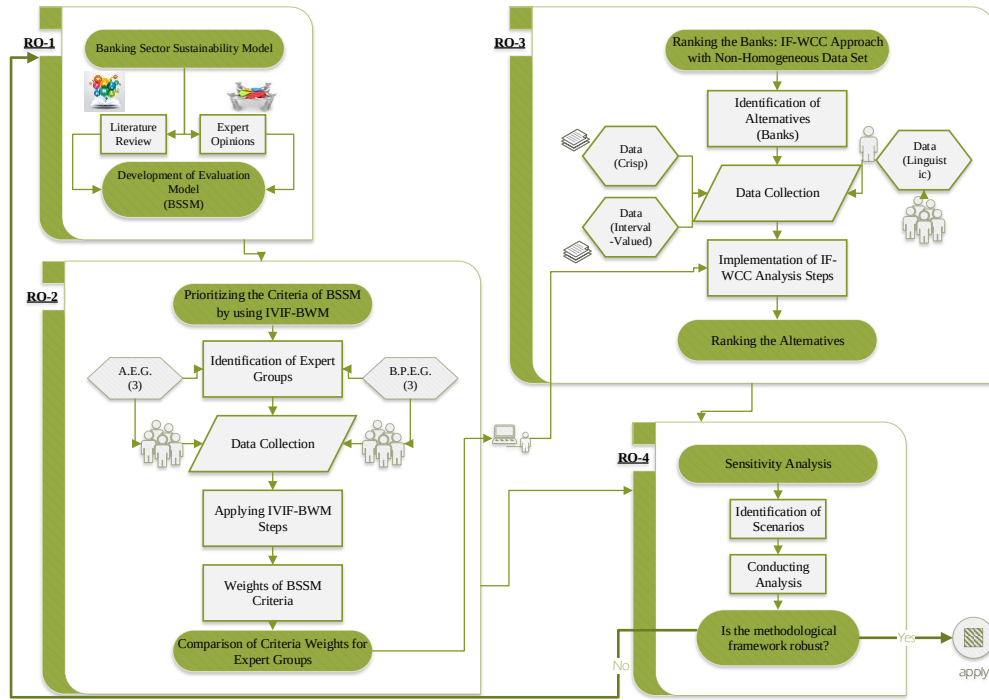


Figure 2. Research Framework

4.1. Prioritizing the Criteria of BSSM by Using IVIF-BWM

Based on literature reviews and expert opinions, it was concluded that the criteria within the proposed BSSM vary in importance and do not carry equal weights. To capture diverse perspectives, consultations were conducted with two expert groups, three academics (A.E.G.) and three banking professionals (B.P.E.G.), revealing notable differences between these groups. To handle the uncertainty in their linguistic assessments, the IVIF-BWM was employed. The study was conducted in accordance with research and publication ethics, with approval obtained from the Nevşehir Hacı Bektaş Veli University Ethics Committee (09/08/2022, 08, 261). The expert panel included four males and two females with 8 to 16 years of professional experience and educational backgrounds ranging from bachelor's to doctoral degrees. The experts provided linguistic evaluations through consensus reached in brainstorming sessions. They were asked questions such as, “Which criterion is most important and which is least important for evaluating a bank’s sustainability performance?” Following consensus, they rated the most important criterion against others, and the remaining criteria relative to the least important, using linguistic terms outlined in Table 1.

Table 1. Linguistic Scale for Pairwise Comparisons

Linguistic Term	IVIF Number Equivalent
Equally Important (EI)	[[1.0,1.0],[0.0,0.0]]
Weakly Important (WI)	[[0.5,0.6],[0.3,0.4]]
Strongly Important (SM)	[[0.6,0.7],[0.2,0.3]]
Very Important (VI)	[[0.7,0.8],[0.1,0.2]]
Absolutely Important (AI)	[[0.8,0.9],[0.1,0.2]]

Source: Wang et al., 2021.

Subsequently, pairwise comparison questionnaires were completed using linguistic terms derived through a brainstorming approach by A.E.G. These linguistic assessments were then translated into IVIF numbers based on the scale provided in Table 1. To determine the optimal weights of the BSSM criteria from the perspective of the academic expert group, the collected data were processed accordingly. Utilizing Model 1 as a foundation, a corresponding model was developed for the main criteria set. In a similar manner, separate models were formulated for each set of main and sub-criteria.

$$\begin{aligned}
 & \min = z; \\
 & @abs(x4L+y1L-x4L*y1L-0.6) \leq z; @abs(x4U+y1U-x4U*y1U-0.7) \leq z; @abs(y4L+x1L-0.2) \leq z; \\
 & @abs(y4U+x1U-0.3) \leq z; @abs(x4L+y2L-x4L*y2L-0.6) \leq z; @abs(x4U+y2U-x4U*y2U-0.7) \leq z; \\
 & @abs(y4L+x2L-0.2) \leq z; @abs(y4U+x2U-0.3) \leq z; @abs(x4L+y3L-x4L*y3L-0.7) \leq z; @abs(x4U+y3U- \\
 & x4U*y3U-0.8) \leq z; @abs(y4L+x3L-0.1) \leq z; @abs(y4U+x3U-0.2) \leq z; @abs(x4L+y5L-x4L*y5L- \\
 & 0.6) \leq z; @abs(x4U+y5U-x4U*y5U-0.7) \leq z; @abs(y4L+x5L-0.2) \leq z; @abs(y4U+x5U-0.3) \leq z; \\
 & @abs(x4L+y6L-x4L*y6L-0.5) \leq z; @abs(x4U+y6U-x4U*y6U-0.6) \leq z; @abs(y4L+x6L-0.3) \leq z; \\
 & @abs(y4U+x6U-0.4) \leq z; @abs(x1L+y3L-x1L*y3L-0.5) \leq z; @abs(x1U+y3U-x1U*y3U-0.6) \leq z; \\
 & @abs(y1L+x3L-0.3) \leq z; @abs(y1U+x3U-0.4) \leq z; @abs(x2L+y3L-x2L*y3L-0.5) \leq z; @abs(x2U+y3U- \\
 & x2U*y3U-0.6) \leq z; @abs(y2L+x3L-0.3) \leq z; @abs(y2U+x3U-0.4) \leq z; @abs(x4L+y3L-x4L*y3L- \\
 & 0.7) \leq z; @abs(x4U+y3U-x4U*y3U-0.8) \leq z; @abs(y4L+x3L-0.1) \leq z; @abs(y4U+x3U-0.2) \leq z; \\
 & @abs(x5L+y3L-x5L*y3L-0.5) \leq z; @abs(x5U+y3U-x5U*y3U-0.6) \leq z; @abs(y5L+x3L-0.3) \leq z; \\
 & @abs(y5U+x3U-0.4) \leq z; @abs(x6L+y3L-x6L*y3L-0.6) \leq z; @abs(x6U+y3U-x6U*y3U-0.7) \leq z; \\
 & @abs(y6L+x3L-0.2) \leq z; @abs(y6U+x3U-0.3) \leq z; x1L+x1U-y1L-y1U > 0; x1L+x1U-y1L-y1U < 2; \\
 & x2L+x2U-y2L-y2U > 0; x2L+x2U-y2L-y2U < 2; x3L+x3U-y3L-y3U > 0; x3L+x3U-y3L-y3U < 2; x4L+x4U- \\
 & y4L-y4U > 0; x4L+x4U-y4L-y4U < 2; x5L+x5U-y5L-y5U > 0; x5L+x5U-y5L-y5U < 2; x6L+x6U-y6L- \\
 & y6U > 0; x6L+x6U-y6L-y6U < 2; (x1L+x1U-y1L-y1U)+(x2L+x2U-y2L-y2U)+(x3L+x3U-y3L- \\
 & y3U)+(x4L+x4U-y4L-y4U)+(x5L+x5U-y5L-y5U)+(x6L+x6U-y6L-y6U) = 2; x1U+y1U \leq 1; \\
 & x2U+y2U \leq 1; x3U+y3U \leq 1; \\
 & x4U+y4U \leq 1; x5U+y5U \leq 1; x6U+y6U \leq 1; x1L < x1U; y1L < y1U; x2L < x2U; y2L < y2U; x3L < x3U; \\
 & y3L < y3U; x4L < x4U; y4L < y4U; x5L < x5U; y5L < y5U; x6L < x6U; y6L < y6U; \\
 & \text{end}
 \end{aligned}$$

The models were solved using the Lingo 19.0 software package, which also facilitated the computation of IVIF values. To assess the consistency of the pairwise comparisons, the BWM-Solver was employed. The consistency ratios for all comparisons were found to be within acceptable thresholds, indicating that the decision-makers provided coherent and reliable evaluations. As an illustration, the results obtained from Lingo 19.0 for the main criteria set (SIGEEF) are presented below:

$$\begin{aligned}
 \tilde{\omega}_S &= ([0.2821, 0.3026], [0.2000, 0.2598]) \\
 \tilde{\omega}_I &= ([0.2821, 0.3026], [0.2000, 0.2598]) \\
 \tilde{\omega}_G &= ([0.2015, 0.2417], [0.1622, 0.2809]) \\
 \tilde{\omega}_E &= ([0.5208, 0.5808], [0.0000, 0.0598]) \\
 \tilde{\omega}_{Ec} &= ([0.2821, 0.3026], [0.2000, 0.2598]) \\
 \tilde{\omega}_F &= ([0.4015, 0.4417], [0.1000, 0.1598])
 \end{aligned}$$

Using the defuzzified criterion weights, summary findings consisting of local and global weights were obtained. Local weights represent the weight and ranking of a criterion within its own criterion set, while global weights reflect the holistic and overall importance of the lowest-level criteria. From the A.E.G. perspective, the importance ranking of the main criteria is as follows: **Environmental (E) (0.2576) > Financial (F) (0.2014) > Social (S) (0.1426) = Innovation (I) (0.1426) = Economic (E) (0.1426) > Governance (G) (0.1134)**. Thus, when examining local weights, the A.E.G. considers the environmental factor as the most important and governance as the least important factor in a bank's sustainability. Furthermore, the ranking of the sub-criteria under the Environmental main criterion according to their importance weights is: **Resource Use (E1) (0.4582) > Waste Management (E3) (0.3507) > Emissions (E2) (0.1912)**. Similarly, for the Social main criterion, the ranking of its sub-criteria is: **Human Rights (S3) (0.4582) > Human Resources (S1) (0.3507) > Social Relations (S2) (0.1912)**. Global weights were also calculated. The criteria with the least importance include Health and Safety Policies, Talent Development Policies, Disabled Employee Ratio, Average Training Duration, Corruption and Bribery Policies, Business Ethics, Employee Volunteering, and External Audit Quality. Criteria with high importance levels include Non-Discrimination, Ease of Banking Transactions, Sustainable Products and Services, Resource Efficiency, Emission Policies, Total CO2 Emission, Waste Recycling Rate, Bank Income, Capital Structure, Financial Growth, and Net Interest Margin. The criteria identified with the highest importance weights are R&D, Total Waste Amount, and Cash Flow.

All the criterion weighting steps carried out for the A.E.G. were also conducted for the B.P.E.G. From the perspective of the bank professionals, the importance ranking of the main criteria is as follows: **Economic (E) (0.2449) > Environmental (E) (0.1904) = Social (S) (0.1904) > Innovation (I) (0.1337) = Governance (G) (0.1337) > Financial (F) (0.1069)**. Thus, when examining the local weights, the B.P.E.G. considers the economic factor as the most important and the financial factor as the least important for a bank's sustainability. Moreover, the ranking of the sub-criteria under the Economic main criterion according to their importance weights is: **Employment (Ec6) (0.2647) > Contribution to the Economy (Ec1) (0.2239) > Fair Trade (Ec4) (0.1605) > Bank Income (Ec5) (0.1251) > Total Number of Branches (Ec2) (0.1129) = Position in the Financial System (Ec3) (0.1129)**. Similarly, the ranking of the sub-criteria under the Financial main criterion is: **Cash Flow (F4) (0.3157) > Financial Growth (F2) (0.2014) = Risk (F5) (0.2014) > Capital Structure (F1) (0.1426) > Profitability (F3) (0.1388)**. Among all criteria, those with the least importance are Customer Satisfaction, Stakeholder Satisfaction, and Net Interest Margin. Criteria with high importance include Working Conditions, SDG Achievement Rate, Emission Policies, Waste Recycling Rate, Waste Reduction Initiatives, Loans, Support for Startups, Total Number of Branches, Fair Trade, Bank Income, Financial Growth, and Cash Flow. The most important criteria are Sustainable Products and Services, and R&D Employment. Notably, differences emerged between the two expert groups. While the A.E.G. emphasized environmental concerns, B.P.E.G. prioritized economic criteria. Both groups assigned similar weights to Innovation and Governance; however, Social and Financial dimensions were evaluated inversely. These distinctions are illustrated in Appendix 2 (Graphs 1–7), highlighting variations in expert perspectives on sustainability priorities within the banking sector.

As a result of the global weight calculations, several criteria were found to hold minimal importance, while others were identified as important or highly significant. Notably, differences emerged between the two expert groups. These are summarized in Table 2, which categorizes the

criteria according to their global weights. The observed divergence reflects a theoretical–practical distinction: academic experts tend to prioritize systemic, policy-oriented, and environmental dimensions of sustainability, whereas banking professionals emphasize operational, market-driven, and actionable factors. Recognizing and understanding these differing viewpoints is essential for aligning academic research with practical needs, ultimately contributing to more effective and balanced sustainable banking strategies.

Table 2. Least Important, Important and Most Important Criteria

	Academics	Banking Professionals
Least important criteria	Health and Safety Policies, Skill Development Policies, Disabled Employee Ratio, Average Training Duration, Anti-Corruption and Bribery Policies, Business Ethics, Employee Volunteering, External Audit Quality	Customer Satisfaction, Stakeholder Satisfaction, Net Interest Margin
High importance criteria	Non-Discrimination, Ease of Banking Transactions, Sustainable Products and Services., Resource Efficiency, Emission Policies, Total CO2 Emission, Total Recycled Waste Amount, Bank Income, Capital Structure, Financial Growth, Net Interest Margin	Working Conditions, SDG Achievement Rate, Emission Policies, Total Recycled Waste Amount, Waste Reduction Initiatives, Loans, Supports for Startups, Total Number of Branches, Fair Trade, Bank Income, Financial Growth, Cash Flow
The most important criteria	R&D, Total Waste Amount, Cash Flow	Sustainable Products and Services, R&D, Employment

4.2. Ranking the Banks: IF-WCC Approach with Non-Homogeneous Data Set

Measuring the sustainability performance of banks is a challenging process in many respects. In this complex decision-making problem, a dataset comprising *linguistic*, *interval-valued*, and *crisp* numbers data is encountered when attempting to rank alternatives using the BSSM. Banks were selected based on specific sustainability and scale-related criteria. These include being listed in ESG ratings, reporting 2021 data, inclusion in the GRI database and BIST Sustainability Index and a minimum of 500 branches (domestic and international). Additionally, all selected banks were among the largest in Türkiye, each with total assets exceeding 900 billion TL.

In the first phase, data collection was carried out for both crisp and interval-valued criteria. Sources included the Banks Association of Türkiye (primarily for financial and economic indicators), Refinitiv Eikon (for ESG data), and the banks' own sustainability, CSR, annual, or integrated reports, as well as Finbox and the banks' official websites. Following the data collection, expert assessments were conducted to gather linguistic evaluations. A new expert group was formed, consisting of five individuals (three men and two women), including customer relationship managers, headquarters professionals, and academics with 8 to 16 years of professional experience and diverse educational backgrounds (undergraduate to doctoral level). Using a brainstorming approach, the experts jointly provided evaluations of the banks based on linguistic terms defined in the scale presented in Table 3. This process yielded the complete raw dataset necessary for analysis.

To enable the transformation of heterogeneous data in the decision matrix into intuitionistic fuzzy numbers (IFNs), several transformation formulas were developed. These formulas allow for the uniform conversion of crisp, interval-valued, and linguistic data into IFNs, facilitating the consistent application of the proposed methodology. Let $A = \{A_1, A_2, \dots, A_m\}$ represent the set of alternatives, and $C = \{C_1, C_2, \dots, C_n\}$ represent the set of criteria. The decision matrix for each expert $D_{(m \times n)}^{(k)} = (a_{ij})_{(m \times n)}^{(k)}$ contains heterogeneous entries (a_{ij}) , corresponding to different data types. The formulas used for these transformations based on the type of heterogeneous data are provided in Table 3 and Table 4. For criteria values that cannot be expressed using crisp number data, linguistic terms are often employed. Expressions such as *very high*, *high*, or *very low* allow decision-makers to evaluate alternatives according to the criteria without difficulty. Accordingly, data obtained in linguistic form can be easily converted into IFNs using the conversion scale provided in Table 3.

Table 3. Transformation of Linguistic Terms into Intuitionistic Fuzzy Numbers (IFNs)

Linguistic Term	IF Number Equivalent
Very High (VH)	(0.80, 0.10, 0.10)
High (H)	(0.70, 0.20, 0.10)
Slightly High (SH)	(0.60, 0.30, 0.10)
Medium (M)	(0.50, 0.40, 0.10)
Slightly Low (SL)	(0.40, 0.50, 0.10)
Low (L)	(0.25, 0.60, 0.15)
Very Low (VL)	(0.10, 0.75, 0.15)

Source: Cavallaro et al., 2018.

In some cases, criterion values for alternatives can be expressed as crisp numbers, such as costs or distances. However, in other situations, rather than a specific value, the criterion may be defined within a certain range. When such cases occur, the transformation formulas provided in Table 4 can be applied to easily convert all data into IFNs, thereby transforming the heterogeneous decision matrix into a homogeneous format suitable for further analysis.

To rank the banks based on their sustainability performance, a raw dataset table was constructed. Upon completing the raw dataset, the classification of the 60 criteria as either benefit criteria (to be maximized) or cost criteria (to be minimized) was determined through expert consultation and a detailed literature review. Following this, the second step involved transforming the raw data into a uniform format based on the type of data as follows: (1) Linguistic terms were converted into IFNs using the scale provided in Table 3; (2) Interval-valued criteria scores (e.g., A^+ , A , A^- , ..., D , D^-) were first transformed into interval values $[L, U]$ using Table 5, and then into IFNs using Equations 8, 9, 10, and 11 in Table 4, depending on whether the criterion was a benefit or cost type; (3) Lastly, crisp numerical data (e.g., tons, Turkish Lira, ratios, quantities, hours, m^3 , tCO₂e) were converted into IFNs using Equations 6 and 7 in Table 4, again based on whether each criterion was classified as a benefit or cost.

Table 4. Transformation of Crisp and Interval-Valued Numbers into Intuitionistic Fuzzy Numbers (IFNs)

Data Type	Criteria Type	Formulation	Eq. No.
Crisp $\rightarrow$ IFN	Benefit	$b_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^n (a_{ij})^2}}$	(6)
	Cost	$b_{ij} = \frac{1/a_{ij}}{\sqrt{\sum_{i=1}^n (1/a_{ij})^2}}$	(7)
*Thus, crisp numbers are converted into IFNs as follows: $\mu_{ij} = b_{ij}$, $v_{ij} = 1 - b_{ij}$, $\pi_{ij} = 0$			
Interval-valued $\rightarrow$ IFN	Benefit	$b_{ij}^L = \frac{a_{ij}^L}{\sqrt{\sum_{i=1}^n (a_{ij}^U)^2}}$	(8)
		$b_{ij}^U = \frac{a_{ij}^U}{\sqrt{\sum_{i=1}^n (a_{ij}^L)^2}}$	(9)
	Cost	$b_{ij}^L = \frac{1/a_{ij}^L}{\sqrt{\sum_{i=1}^n (1/a_{ij}^U)^2}}$	(10)
		$b_{ij}^U = \frac{1/a_{ij}^U}{\sqrt{\sum_{i=1}^n (1/a_{ij}^L)^2}}$	(11)
* Thus, IVNs are converted into IFNs as follows: $\mu_{ij} = b_{ij}^L$, $v_{ij} = 1 - b_{ij}^U$, $\pi_{ij} = b_{ij}^U - b_{ij}^L$			
Source: Guo, 2013.			

Source: Guo, 2013.

Through the transformation of all heterogeneous data into homogeneous data (i.e., IFNs), normalization was achieved, ensuring that all values fell within the [0,1] interval, and the subsequent steps of the analysis were carried out by constructing the intuitionistic fuzzy decision matrix.

Table 5. Transformation of Qualitative Scores into Numerical Interval Values [L , U]

Score	L	U
A+	0.9166	1
A	0.8333	0.9166
A-	0.75	0.8333
B+	0.6666	0.75
B	0.5833	0.6666
B-	0.5	0.5833
C+	0.4166	0.5
C	0.3333	0.4166
C-	0.25	0.3333
D+	0.1666	0.25
D	0.0833	0.1666
D-	0	0.0833

Source: Refinitv. 2022.

Additionally, IFSs and IFNs are designed to handle uncertainty. Even though some of the original data consisted of crisp numbers, it was observed that certain criterion values for the same bank were reported differently across various sources. To address this issue, converting such data

into IFNs ensured the accuracy of the analysis results and justified the necessity of IFN transformation. In the final step, WCC values were calculated to rank the banks based on their sustainability performance. These calculations were conducted using Equation 5. Furthermore, in the computations, the criterion weights obtained from the IVIF-BWM based on the assessments of banking professionals were employed. After performing all necessary calculations, the WCC values and the corresponding bank rankings in terms of sustainability performance were determined. These results are presented in Table 6. As shown in Table 6, Bank 1 ranks first with a WCC value of 0.799208, followed by Bank 4. Bank 3 and Bank 2. No significant differences were observed among the WCC values. This is primarily due to the fact that all four banks included in the analysis are among the leading institutions in Turkey in terms of their commitment to sustainability efforts.

Table 6. Ranking of Banks Based on Sustainability Performance

Alternatives	WCC Value	Rank
Bank 1	0.799208	1
Bank 2	0.632505	4
Bank 3	0.718258	3
Bank 4	0.758665	2

Source: Authors' own creation.

4.3. Sensitivity Analysis

Sensitivity analysis is a methodological tool used to examine how variations in input data affect the outcomes of a decision-making model. In the context of MCDM, sensitivity analysis typically involves assessing how changes in the weights assigned to criteria influence the ranking of alternatives. This step is crucial in validating the robustness and reliability of the results obtained from such models. Different approaches have been adopted in the literature for conducting sensitivity analyses. For instance, Çelik et al. (2022) employed a one-dimensional sensitivity analysis in their study. In this approach, the weight of the most important criterion is varied within a suitable range, while the remaining criteria weights are distributed equally. The formula used to determine the appropriate range for adjusting the most significant criterion's weight is derived from the work of Karande et al. (2016). Another approach is provided by Michailidou et al. (2016), who developed six distinct scenarios by increasing and decreasing the original criterion weights by 10%, 20%, and 30%, respectively. These variations were then compared with the baseline scenario to analyze the degree of fluctuation in the results. Similarly, Mishra et al. (2021) proposed a model involving nine criteria and performed a rotational sensitivity analysis across nine scenarios. In each scenario, a different criterion was assumed to be the most important by assigning it a higher weight, while the weights of other criteria were adjusted accordingly. This cyclic approach allowed them to observe changes in alternative rankings under all possible dominant-weight conditions and provided insights into the stability of rankings when each criterion's weight shifts from its minimum to maximum value. In another study, Şimşek Yağlı and Zengin Taşdemir (2023) used the weights obtained from the BWM as the baseline scenario. They then compared this with an equal-weight scenario and eight additional scenarios. In each of the eight, one criterion was given a dominant weight of 0.50, and the remaining five criteria were assigned equal shares of the residual weight. This approach enabled a comparative assessment of the model's sensitivity under highly skewed weight distributions.

Building upon these established methodologies, the current study developed ten distinct sensitivity scenarios to test the robustness of the results and to evaluate the potential impact of data uncertainty or inconsistencies in expert judgments. These scenarios include:

Scenario 1–2: Weight vectors obtained from the IVIF-BWM method based on two separate expert groups (professionals and academics);

Scenario 3: Weighting based on the Shannon Entropy method;

Scenario 4: Equal weighting of all main criteria;

Scenarios 5–10: Each of the six main criteria in the SIGEEF framework was individually assigned a dominant weight of 0.50, while the remaining five were each assigned weights of 0.10.

This comprehensive sensitivity analysis framework enhances the credibility of the model by revealing the stability or volatility of rankings across various weighting assumptions. It also demonstrates the model's capability to accommodate expert opinion variability and potential data imperfections. The results of the sensitivity analysis, illustrated in Figure 3 through a radar chart, indicate that the ranking of alternatives remained largely consistent across the ten evaluated scenarios. Minor deviations were observed in Scenario 3 and Scenario 8; however, in 80% of the scenarios, similar ranking patterns were maintained. Bank 1 predominantly ranked first, while Bank 2 consistently appeared in the last position. These findings confirm the reliability, robustness, and practical applicability of the proposed methodological framework, even under varying weighting schemes and potential uncertainty in expert judgments.

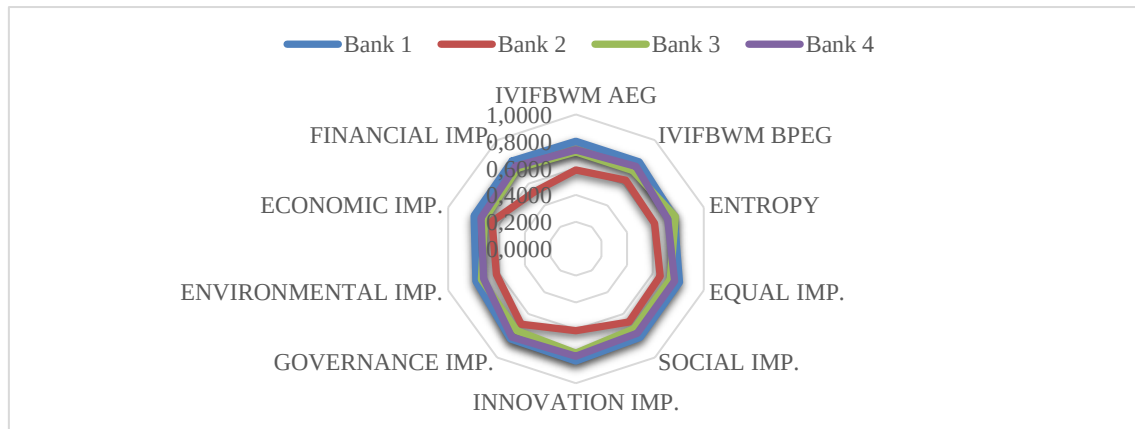


Figure 3. Radar Plot of Alternative Rankings Across Sensitivity Scenarios

5. Conclusions and Discussions

The banking sector, given its cross-sectoral influence, plays a pivotal role in shaping sustainable development. Therefore, there is a growing need for banks to assess their own sustainability performance and to benchmark themselves against industry peers. Such evaluations are critical for identifying areas of improvement, developing competitive strategies, and ensuring long-term success. However, sustainability performance evaluation in banking is inherently complex, involving diverse and sometimes conflicting economic, social, environmental, legal, ethical, and financial considerations (Stefanova. 2019). To address this complexity, this study introduces a novel methodological framework. The BSSM was established using major theories

(such as Stakeholder Theory, TBL, and Institutional Theory), significant literature study, and interaction with domain experts, and it provides a layered, multidimensional structure for assessing sustainability. The model comprises six main criteria; Social, Innovation, Governance, Environmental, Economic, and Financial (SIGEEF), supported by 23 second-level sub-criteria and 60 third-level indicators. This hierarchical structure facilitates clearer categorization and evaluation, enabling more effective decision-making.

Given the unequal importance of these criteria, the study utilizes a weighting process based on the BWM integrated with interval-valued intuitionistic fuzzy sets. This hybrid approach captures expert judgments under uncertainty and imprecision. The evaluation was conducted with input from two expert perspectives: the academics and the banking professionals expert groups, respectively. The results indicate varying perspectives: A.E.G. prioritized the environmental dimension (weight: 0.2576), followed by financial and social aspects, whereas B.P.E.G. considered the economic dimension most important (weight: 0.2449), with environmental and social factors ranked equally. Governance and financial criteria were deemed least important by each group, respectively. Here, Institutional and Stakeholder Theory can be used to analyze the differences between professional and academic experts. Operating within a normative framework, academic experts typically prioritize governance and environmental issues, reflecting long-term social expectations. On the other hand, banking professionals are more impacted by market and coercive forces, focusing on financial and economic aspects to maintain operational stability and competitiveness. This implies that, to reconcile theoretical aspirations with real-world realities, there needs to be greater alignment between sustainability concepts and banking practice. Moreover, these differences underscore the necessity for enhanced collaboration among stakeholders to align priorities and optimize resource allocation. Effective banking efforts to promote sustainability must therefore close this gap by utilizing incentive programs, integrated policy frameworks, and ESG-linked financial products that match theoretical goals with real-world application.

This study provides several valuable theoretical and practical contributions to the field of sustainability performance evaluation, particularly within the context of the banking sector. First, the model developed, namely, the BSSM, represents a novel approach that addresses the lack of a comprehensive, sector-specific model tailored to the unique dynamics of the banking industry. By incorporating a multi-dimensional and hierarchical structure, the BSSM enables nuanced assessments across various sustainability dimensions and supports both academic research and managerial decision-making. From a theoretical standpoint, the study expands on the traditional TBL framework and Stakeholder theory by incorporating ideas from institutional and dynamic capability into a multifaceted framework designed especially for banking. Furthermore, the findings imply that the observed discrepancies have important ramifications for sustainable finance governance. Banks that prioritize economic and financial aspects, for instance, run the danger of underfunding long-term social or environmental projects. On the other hand, stability may be jeopardized if environmental concerns are overemphasized without being financially feasible. Thus, a well-rounded strategy based on the multifaceted SIGEEF framework can aid in resolving these conflicting priorities and promoting stakeholder alignment. Second, the application of the BSSM using real-world data demonstrates the model's practical relevance and usability. It shows that banks can utilize the framework to benchmark their performance, identify areas of strength and weakness, and develop actionable strategies for improvement. The model's structure also allows for the disaggregation of sustainability into distinct dimensions, SIGEEF,

thereby enabling focused evaluations and the development of sub-models tailored to each dimension. Moreover, the framework is designed to be compatible with various MCDM techniques, facilitating methodological flexibility and comparability across studies. Third, the integration of expert opinions from both academic and professional domains enhances the validity of the model. Considering different stakeholder perspectives helps to fill potential information gaps and ensures that the model reflects diverse expectations and realities. This multi-stakeholder approach not only strengthens the robustness of the evaluation process but also fosters collaboration in sustainability planning. From a practical perspective, the use of multiple quantitative methods, including the IVIF-BWM and IF-WCC, enhances the credibility and objectivity of the evaluation results. These methods support the derivation of measurable, transparent, and reproducible outcomes, which are critical for building trust and comparability in sustainability assessments. Importantly, the identification of the relative importance of evaluation criteria provides decision-makers with critical insights into how to prioritize initiatives and allocate scarce resources effectively. At the same time, the observed differences in criteria importance between academic and industry experts highlight the need for continuous dialogue to reconcile divergent views and develop shared priorities. Furthermore, the BSSM enables banks to position themselves competitively within the sector by identifying their relative performance rankings and taking necessary actions to enhance their sustainability standing. This capability supports long-term strategic planning and may contribute to the development of competitive advantages (Nizam et al., 2019). Based on the evaluation outcomes, banks can also implement tailored training programs, develop internal policies, and revise operational procedures to address specific performance gaps. Moreover, the structured definition of criteria using different data types, crisp, linguistic, and interval-valued, also provides guidance for future data collection and helps standardize sustainability reporting. The adoption of quantitative, fuzzy-based approaches further enhances the reliability of evaluations, enabling robust benchmarking and facilitating informed decision-making. Although the BSSM was specifically designed for the banking sector, its adaptable structure allows for modification of criteria, making it a flexible and scalable tool applicable for sustainability assessment in other sectors as well. The BSSM-based rankings allow banks to pinpoint areas that need improvement in terms of policy and strategic implications. By increasing stakeholder involvement, investing in the community, or implementing green financing programs, banks with poor social or environmental scores can improve their sustainability profiles. In a similar vein, regulatory bodies can use these rankings to create focused sustainability disclosure guidelines, which will increase responsibility and openness in the industry. Overall, the findings highlight how crucial multi-stakeholder cooperation and context-sensitive assessment methods are to creating a robust and sustainable banking environment. In summary, the BSSM advances the discourse on sustainable banking by providing a theoretically grounded, empirically validated, and practically applicable model that supports informed decision-making, accountability, and strategic sustainability transformation within the financial sector. In this way, it can be stated that all research objectives have been achieved.

As with any empirical research, this study is subject to several limitations. The first limitation lies in the sector-specific nature of the proposed methodological framework. Although it is theoretically adaptable to other sectors through appropriate updates and modifications, the current implementation is limited to the banking industry. Therefore, the generalizability of the findings should be interpreted within this context. The second limitation concerns the challenges encountered in gathering expert opinions. Limited availability of experts and time constraints

made data collection particularly demanding. Another significant limitation involves access to data. While financial information from banks is generally accessible, sustainability-related data, especially in the areas of social, governance, and environmental performance, are often either not reported or remain incomplete. Consequently, the application phase of the model was restricted to only four banks due to these data limitations. A further limitation concerns the subjective nature of some data inputs within the framework, particularly those used in weighting and ranking processes. As such, the results may vary depending on temporal, geographical, sectoral, or individual differences in expert judgment.

Based on these limitations, several suggestions are offered for future research. First, once data accessibility challenges are mitigated, the model should be applied across a broader sample encompassing the entire banking sector. Second, the robustness and validity of the proposed framework can be further tested by employing alternative MCDM techniques. Third, the framework could be revised and applied to other sectors by adapting the criteria to suit sector-specific sustainability dynamics. Future research may empirically test the theoretical linkages between the SIGEEF dimensions and firm performance. Finally, future studies may consider integrating alternative fuzzy set extensions into the methodology to enrich the analytical depth and interpretability of results.

Declaration of Research and Publication Ethics

Ethical approval for the study were obtained from Nevşehir Hacı Bektaş Veli University Ethics Committee (Date: 09/08/2022, No: 08, Decision No: 261). This study complies with research and publication ethics.

Researcher’s Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest

There are no potential conflicts of interest in this study.

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APPENDIX

Table A1. BSSM criteria and its references

1	Main Criteria		References
	1. Sub- Criteria	2. Sub- Criteria	
1- SOCIAL (S)			
(S1)	Human Resources	(S1-1) Health and Safety Policies	(ESG – GRI – TBL – Aras et al., 2018 – Kilic et al., 2015 – Taşkın, 2015 – Ecer, 2019 – Karagiorgos, 2010 – Oliveira et al., 2019 – Govindan et al., 2014 – Rebai et al., 2016 – Ömürbek et al., 2017 – Sobhani et al., 2012 – Ahmadi et al., 2017)
		(S1-2) Education and Development Policies	
		(S1-3) Skill Development Policies	
		(S1-4) Average Employee Income *	
		(S1-5) Female Employee Ratio *	
		(S1-6) Female Executive Ratio *	
		(S1-7) Disabled Employee Ratio *	
		(S1-8) Employee Turnover Rate *	
		(S1-9) Average Training Duration *	
		(S1-10) Promotions	
		(S1-11) Employee Satisfaction	
(S2)	Social Relationships	(S2-1) Anti-Corruption and Bribery Policy	
		(S2-2) Business Ethics	
		(S2-3) Community Engagement	
		(S2-4) Donations *	
		(S2-5) Employee Volunteering	
		(S2-6) Customer Satisfaction	
(S3)	Human Rights	(S3-1) Working Conditions	
		(S3-2) Non-Discrimination	
		(S3-3) Work-Life Balance	
		(S3-4) Equal Opportunity	
2- INNOVATION (I)			
(I1)	Digitalization	(I1-1) Internet Banking Quality	(ESG – Goyal et al., 2015 – Kilic et al., 2015 – Karaman and Akman, 2018 – Ahmed et al., 2012 – Korzeb et al., 2019 – Govindan, 2022)
		(I1-2) Mobile Banking Quality	
		(I1-3) Ease of Banking Transactions	
		(I1-4) Total Number of ATMs *	
(I2)	Sustainable Products And Services		
(I3)	R &D *		
3- GOVERNANCE (G)			
(G1)	Management	(G1-1) Corporate Governance Structure	(ESG – Govindan et al., 2014 – Rafinda et al., 2018 – Szegedi et al., 2020 – Ahmed et al., 2012 – Aras et al., 2018)
		(G1-2) Independent Board Member Rate *	
		(G1-3) Female Board Member Rate *	
		(G1-4) Internal Audit Quality	
		(G1-5) Crisis Management System	
(G2)	Stakeholders	(G2-1) Responsible Marketing Policies	
		(G2-2) Customer Privacy	
		(G2-3) Data Security	
		(G2-4) Stakeholder Satisfaction	
(G3)	CSR Strategy	(G3-1) CSR Management	
		(G3-2) External Audit Qualiyy	
		(G3-3) SDG Achievement Rate *	
		(G3-4) Effective Sustainability Communication	

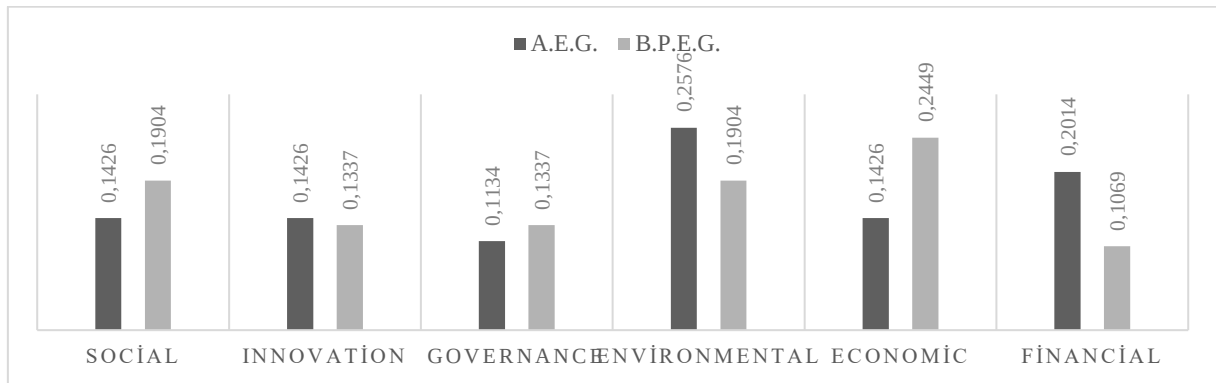
Table A1. Continued

4- ENVIRONMENTAL (E)				
(E1)	Resource Usage	(E1-1)	Resource Efficiency	(ESG – TBL – GRI – Aras et al., 2018 – Ecer, 2019 – Govindan et al., 2014 – Sobhani et al., 2012)
		(E1-2)	Environment Management Team	
		(E1-3)	Environment Management Training	
		(E1-4)	Total Energy Consumption *	
(E2)	Emissions	(E1-5)	Total Water Consumption *	
		(E1-6)	Total Paper Consumption *	
		(E2-1)	Emission Policies	
		(E2-2)	Total CO ₂ Emission *	
(E3)	Waste Management	(E3-1)	Total Waste Amount *	
		(E3-2)	Total Recycled Waste Amount *	
		(E3-3)	Waste Reduction Initiatives	
5- ECONOMIC (E)				
(Ec1)	Contribution to the Economy	(Ec1-1)	Loans *	(TBL – GRI – Aras et al., 2018 – Ecer, 2019 – Rebai et al., 2016 – Goyal et al., 2015 – Taskin, 2015 – Sustainable Work Awards – Ömürbek et al., 2017 – Mallin et al., 2014)
(Ec2)	Total Number of Branches *	(Ec1-2)	Supports for StartUps	
(Ec3)	Position in the Financial System	(Ec3-1)	Total Assets *	
		(Ec3-2)	Total Loans *	
		(Ec3-3)	Total Deposits*	
(Ec4)	Fair Trade			
(Ec5)	Bank Income *			
(Ec6)	Employment *			
6- FINANCIAL (F)				
(F1)	Capital Structure *			(TBL – Aras et al., 2018 – Omurbek et al., 2017 – Ecer, 2019 – Ozcelik et al., 2014 – Govindan et al., 2014 – Taskin, 2015 – Karagiorgos, 2010 – Rafinda et al., 2018)
(F2)	Financial Growth *			
(F3)	Profitability *	(F3-1)	Return on Equity (ROE) *	
		(F3-2)	Return on Assets (ROA) *	
		(F3-3)	Net Interest Margin *	
(F4)	Cash Flow *			
(F5)	Risk	(F5-1)	Financial Risk Management	
		(F5-2)	CAPM Beta *	
		(F5-3)	Altman Z Score *	

(ESG – TBL – GRI – Aras et al., 2018 – Ecer, 2019 – Govindan et al., 2012)

(TBL – GRI – Aras et al., 2018 – Ecer, 2019 – Rebai et al., 2016 – Goyal et al., 2015 – Taskin, 2015 – Sustainable Work Awards – Ömürbek et al., 2017 – Mallin et al., 2014)

(TBL – Aras et al., 2018 – Omurbek et al., 2017 – Ecer, 2019 – Ozcelik et al., 2014 – Govindan et al., 2014 – Taskin, 2015 – Karagiorgos, 2010 – Rafinda et al., 2018)



Graph A1. Comparison of Main Criteria Weights



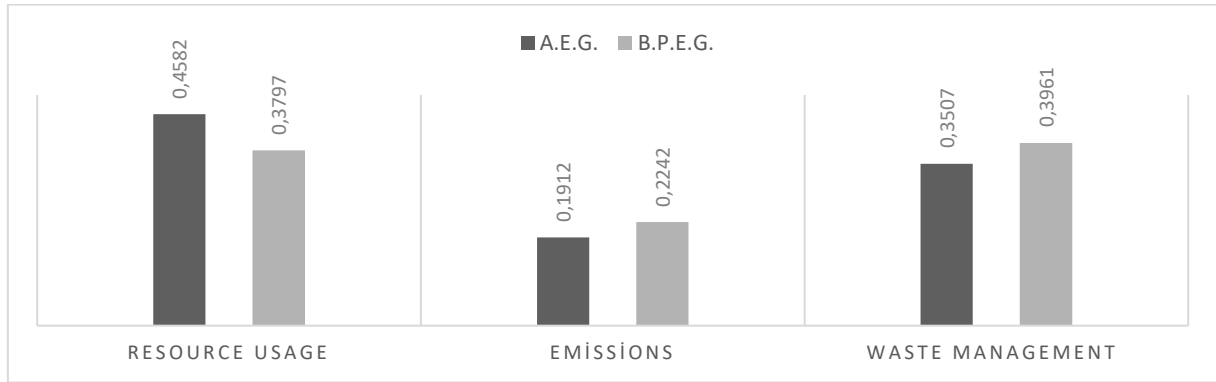
Graph A2. Comparison of Sub-Criterion Weights for the Social Criterion



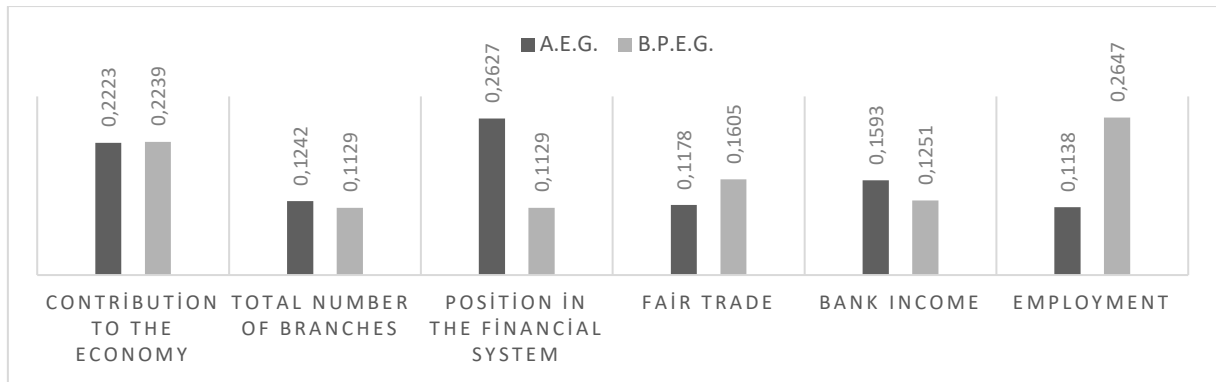
Graph A3. Comparison of Sub-Criteria Weights for the Innovation Criterion



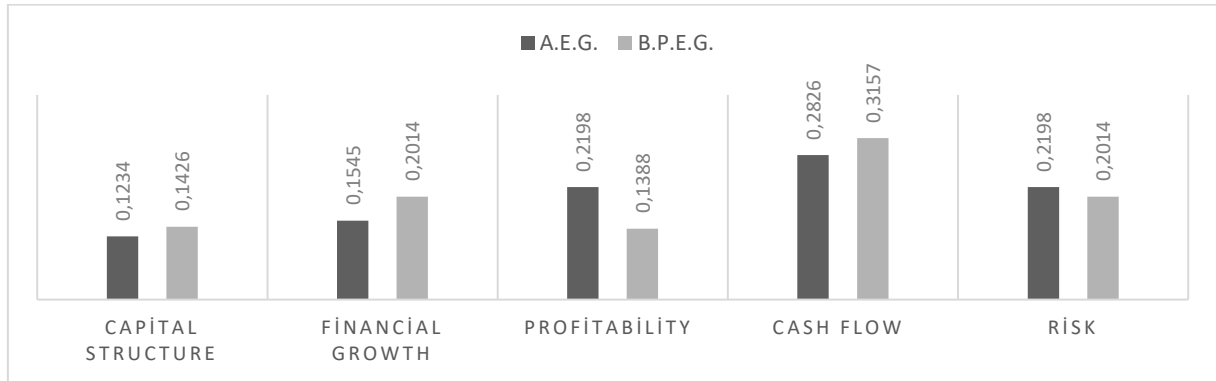
Graph A4. Comparison of Sub-Criteria Weights under the Governance Criterion



Graph A5. Comparison of the Weights of Sub-Criteria under the Environmental Criterion



Graph A6. Comparison of Sub-Criteria Weights for the Economic Criterion



Graph A7. Comparison of Sub-Criteria Weights for the Financial Criterion

EVALUATING ESG SUSTAINABILITY PERFORMANCE IN THE TURKISH BANKING INDUSTRY: A GREY LOPCOW–MSD–PIV APPROACH

Türk Bankacılık Sektöründe ESG Sürdürülebilirlik Performansının
Değerlendirilmesi: Gri LOPCOW–MSD–PIV Yaklaşımı

Berrak TEKGÜN* 

Abstract

This study introduces a novel grey-based multi-criteria decision-making (MCDM) framework designed to assess the Environmental, Social, and Governance (ESG) sustainability performance of banks listed on Borsa İstanbul (BIST). The suggested hybrid grey-based model integrates two objective weighting techniques—Grey Logarithmic Percentage Change-Driven Objective Weighting (G-LOPCOW) and Grey Modified Standard Deviation (G-MSD)—with the Grey Preference Index Value (G-PIV) ranking procedure to effectively manage epistemic uncertainty inherent in sustainability data. Ten ESG indicators obtained from the Refinitiv Eikon database for the 2021–2023 period form the analytical foundation of the sustainability assessment. The integrated weighting process identifies community engagement, product responsibility, and shareholder relations as the most influential determinants shaping banks' sustainability profiles. Based on the G-PIV results, İşbank, Yapı Kredi, and TSKB rank as the top-performing institutions. The empirical findings not only provide valuable insights into the ESG positioning of Turkish banks but also offer a replicable methodological framework for practitioners and policymakers seeking data-driven sustainability benchmarking. Furthermore, the study contributes to the growing body of literature on grey system-based decision models, reinforcing their utility in addressing ambiguity and partial information in complex financial and sustainability evaluations.

Keywords:

ESG
Sustainability,
G-LOPCOW,
G-MSD,
G-PIV,
Grey System
Theory,
Turkish banks

JEL Codes:

G21, M21,
Q56, C44.

Öz

Bu çalışma, Borsa İstanbul'da (BIST) işlem gören bankaların Çevresel, Sosyal ve Yönetişim (ESG) sürdürülebilirlik performansını değerlendirmek üzere tasarlanmış yeni bir gri tabanlı çok kriterli karar verme (ÇKKV) çerçevesi sunmaktadır. Önerilen hibrit gri tabanlı model, sürdürülebilirlik verilerinde bulunan epistemik belirsizliği etkin bir şekilde yönetmek için iki nesnel ağırlıklandırma tekniği olan Gri Logaritmik Yüzde Değişim Odaklı Nesnel Ağırlıklandırma (G-LOPCOW) ve Gri Değiştirilmiş Standart Sapma'yı (G-MSD) Gri Tercih Endeksi Değeri (G-PIV) sıralama prosedürüyle birleştirir. Refinitiv Eikon veri tabanından 2021-2023 dönemi için elde edilen on ESG göstergesi, sürdürülebilirlik değerlendirmesinin analitik temelini oluşturmaktadır. Entegre ağırlıklandırma süreci, topluluk katılımını, ürün sorumluluğunu ve hissedar ilişkilerini bankaların sürdürülebilirlik profillerini şekillendiren en etkili belirleyiciler olarak belirlemiştir. G-PIV sonuçlarına göre, İş Bankası, Yapı Kredi ve TSKB en iyi performans gösteren kurumlar olarak sıralanmaktadır. Ampirik bulgular, Türk bankalarının ESG konumlandırmasına dair değerli bilgiler sağlamanın yanı sıra, veri odaklı sürdürülebilirlik kıyaslamasına odaklanan uygulayıcılar ve politika yapıcılar için tekrarlanabilir bir metodolojik çerçeve de sunmaktadır. Ayrıca, çalışma, gri sistem tabanlı karar modelleri hakkındaki giderek artan literatüre katkıda bulunarak, karmaşık finansal ve sürdürülebilirlik değerlendirmelerinde belirsizlik ve kısmi bilginin ele alınmasındaki faydalarını pekiştirmektedir.

Anahtar

Kelimeler:

ESG
Sürdürülebilirliği,
G-LOPCOW,
G-MSD,
G-PIV,
Gri Sistem
Teorisi, Türk
Bankaları.

JEL Kodları:

G21, M21,
Q56, C44.

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1. Introduction

In recent years, Environmental, Social, and Governance (ESG) considerations have become a central pillar of financial and corporate strategy, shaping how institutions create value, manage risk, and interact with society (Akbulut, 2024; Işık and Adalar, 2025; Manta et al., 2025). As global markets shift toward sustainability-oriented growth, banks—acting as the primary channels of financial intermediation—are expected to align their operations with ESG principles to strengthen ethical accountability and long-term resilience (Karki et al., 2025; Mirza et al., 2025).

ESG performance captures how effectively financial institutions internalize sustainability values through environmental stewardship, social responsibility, and governance transparency. Strong ESG practices enhance financial resilience, reinforce market credibility, and mitigate exposure to reputational and regulatory risks (Buallay, 2019; Broadstock et al., 2021; Ersoy et al., 2022; López-Penabad et al., 2023; Dou et al., 2025). Assessing ESG performance in the banking sector is not only a compliance requirement but also a strategic necessity. Financial institutions play a key role in financing low-carbon transitions, fostering financial inclusion, and ensuring responsible corporate conduct throughout the economy (Işık et al., 2025a; Ünlü and Çıtak, 2025; Akbulut and Aydın, 2024). Consequently, a reliable evaluation mechanism enables banks to identify sustainability strengths and weaknesses, guide improvement strategies, and enhance alignment with global initiatives such as the United Nations Sustainable Development Goals (SDGs) and the Principles for Responsible Banking (PRB) (Ecer and Pamucar, 2022).

From a theoretical standpoint, the quantification of ESG performance in banking extends beyond measurement—it reflects the interplay of economic, ethical, and institutional dynamics (Azmi et al., 2021, Ersoy et al., 2022; Işık, 2023; Dohrmann et al., 2024). Stakeholder theory (Freeman, 1984) offers the ethical foundation by asserting that firms sustain long-term value by balancing the interests of all stakeholders—shareholders, employees, customers, regulators, and communities. Within this framework, ESG measurement allows banks to evaluate how effectively they fulfill multi-stakeholder responsibilities and sustain social legitimacy. The resource-based view (Russo and Fouts, 1997) complements this reasoning by interpreting ESG capabilities as strategic resources that can generate enduring competitive advantages. Objective ESG evaluation helps identify which sustainability practices translate into distinctive, inimitable, and value-creating organizational capabilities. Stewardship theory (van Puyvelde et al., 2012) further strengthens this perspective by portraying managers as custodians of corporate value, implying that systematic ESG assessment serves as a governance mechanism that aligns managerial actions with long-term sustainability goals. Finally, legitimacy theory (Suchman, 1995) provides the institutional rationale, arguing that transparent ESG measurement and disclosure reinforce organizational legitimacy in a regulatory environment where social responsibility and compliance expectations continue to intensify. Collectively, these theories justify the need for rigorous and objective ESG performance measurement in banking.

Despite its growing importance, ESG performance assessment remains analytically challenging. ESG frameworks consist of multiple heterogeneous indicators—ranging from emissions and resource efficiency to workforce diversity and board accountability (Işık and Adalar, 2025; Demir, 2025; Yang et al., 2025). These indicators differ in scale, completeness, and precision, complicating their integration into a single composite framework. Furthermore, interdependencies among the three ESG pillars often lead to trade-offs between dimensions, such as when environmental investments temporarily affect social or governance outcomes.

Traditional linear or statistical models fail to fully capture these interactions and the epistemic uncertainty inherent in ESG data, emphasizing the need for a more flexible and uncertainty-tolerant decision framework (Reig-Mullor and Brotons-Martinez, 2021; Hoang et al., 2024; Yu et al., 2024; da Cunha et al., 2025; Lombardi Netto et al., 2025).

To systematically address the epistemic uncertainty inherent in ESG evaluations and to construct a robust and reliable decision-support mechanism tailored to the banking sector, this study develops a novel Multi-Criteria Decision-Making (MCDM) approach grounded in grey system theory. Grey theory, developed by Deng (1982), provides a mathematically consistent structure for analyzing systems with incomplete, imprecise, or uncertain information (Akbulut, 2024; Ulutař et al., 2024; Durdu et al., 2025). It enables robust evaluation even when data are partially disclosed or inconsistent—conditions typical of sustainability datasets (Karadağ Albayrak, 2021). Building upon this theoretical basis, the present research develops an integrated grey-based MCDM framework for the systematic evaluation of ESG sustainability performance among banks.

To empirically validate the proposed grey-based decision framework, a case study was conducted comparing the ESG sustainability performance of nine banks listed on Borsa İstanbul (BIST) over the 2021–2023 period. This timeframe was strategically selected, as it coincides with the institutionalization of sustainability reporting practices in the Turkish banking sector—driven by intensified regulatory focus on climate-related risk disclosures and the broader adoption of sustainable finance principles. ESG data were retrieved from the Refinitiv Eikon database, which offers standardized and internationally comparable indicators suitable for cross-institutional benchmarking. The selected period represents a critical transition phase during which ESG integration progressed from voluntary disclosure to formalized compliance, thereby providing a robust and policy-relevant context for evaluating sustainability performance across banking institutions.

Accordingly, the research questions addressed in the present manuscript are as follows:

RQ1. Which ESG criteria exert the most significant influence on the overall sustainability performance of Turkish banks?

RQ2. How do BIST-listed banks perform in terms of ESG sustainability between 2021 and 2023 when evaluated through an objective, grey-based MCDM framework?

RQ3. Can the proposed Grey LOPCOW–MSD–PIV model serve as a reliable and replicable decision-support mechanism for ESG assessment under uncertainty?

To address the outlined research questions, this work introduces a novel grey-based MCDM framework specifically designed for ESG performance assessment in banking institutions. Within this structure, two objective weighting techniques—Grey Logarithmic Percentage Change-driven Objective Weighting (G-LOPCOW) and Grey Modified Standard Deviation (G-MSD)—are employed to quantify the informational contribution of each ESG criterion from distinct statistical standpoints. G-LOPCOW captures logarithmic sensitivity to proportional changes in grey data, while G-MSD reflects the degree of dispersion across grey interval values, offering a robust measure of variability under uncertainty. The resulting weight vectors are subsequently synthesized using a linear aggregation operator to ensure consistency and minimize potential weighting bias. Finally, the Grey Proximity Indexed Value (G-PIV) integrates the aggregated weights to produce a composite ranking of banks, yielding a decision-

support framework that is interpretable, resilient to data uncertainty, and analytically coherent for ESG sustainability assessment.

This study adds new insights to the MCDM literature and advances empirical approaches to ESG performance assessment in the banking sector from various perspectives. First, the present work introduces a comprehensive and theoretically grounded grey-based MCDM framework for assessing the ESG sustainability performance of banks. Its principal novelty arises from the methodological integration of grey system theory with three complementary analytical components—G-LOPCOW, G-MSD, and G-PIV. This hybrid structure enables a coherent and uncertainty-tolerant assessment process that surpasses the limitations of traditional linear or purely statistical ESG evaluation models. By incorporating grey interval numbers, the suggested approach provides a mathematically consistent foundation for handling epistemic uncertainty, thereby ensuring reliable decision outcomes even when the available data are incomplete, imprecise, or partially known. Second, from a methodological standpoint, the integration of G-LOPCOW and G-MSD represents a dual-objective weighting scheme that combines logarithmic sensitivity and dispersion-based variability under epistemic uncertainty. The linear aggregation of these two weighting schemes produces a balanced and bias-free vector of criterion weights, thus enhancing the objectivity and stability of the decision-making process. The subsequent application of the Grey PIV tool offers a transparent and computationally efficient ranking procedure, which is particularly suitable for sustainability assessments that require interpretability and reproducibility. Third, empirically, this manuscript applies this integrated framework to nine banks listed on BIST for the period 2021–2023, a time frame that marks the institutionalization of sustainability reporting practices in the Turkish banking sector. The use of ESG data from the Refinitiv Eikon database allows for internationally standardized comparison and enhances the external validity of the findings. The results not only shed light on the relative sustainability performance of leading financial institutions but also capture the structural transformation of the sector as it transitions from voluntary ESG disclosure to mandatory sustainability compliance. This empirical validation provides policy-relevant insights for regulators and financial authorities seeking to promote sustainable finance within emerging markets. Finally, theoretically, the developed grey-based hybrid framework contributes to the growing body of MCDM literature by bridging two fundamental logics of objective weighting—information theory and variance-based reasoning—within a unified grey environment. This dual-statistical perspective enriches the methodological toolkit available for researchers dealing with uncertain, heterogeneous, or interval-valued data. Practically, the model provides a decision-support mechanism that is both flexible and generalizable, allowing its application beyond ESG performance analysis to other domains such as corporate governance evaluation, financial resilience measurement, or innovation efficiency assessment.

2. Literature Review

In recent years, the integration of MCDM procedures into performance assessment frameworks has gained substantial momentum, particularly within the domains of banking, finance, and sustainability. These techniques offer a structured and transparent means of assessing organizational performance across both quantitative financial indicators and qualitative non-financial dimensions, such as ESG criteria.

Within the context of banking industry research, MCDM approaches have been increasingly adopted to address the limitations of traditional single-criterion evaluations. By incorporating diverse weighting structure and ranking algorithms, scholars have developed robust models that capture the multi-dimensional nature of bank performance, including profitability, operational efficiency, and sustainability. Notably, recent studies have adopted a diverse range of hybrid and fuzzy-augmented MCDM techniques to evaluate banking performance across multiple dimensions. These applications not only enhance decision transparency but also support comparative benchmarking across institutions and regions.

Table 1 provides a comprehensive synthesis of recent empirical studies that utilize MCDM methodologies to assess firm-level performance in the banking sector, highlighting the diversity of methodological configurations and evaluation scopes.

Table 1. Multidimensional Firm Performance Assessments via MCDM Approaches

Study	Bank	Weighting Methodology	Ranking Procedure	Scope
Akbulut (2019)	İřbank	CRITIC	EDAS	Assessment of financial performance
Reig-Mullor and Brotons-Martinez (2021)	Spanish commercial banks	IF-AHP	IF-TOPSIS	Evaluating sustainability and financial health
Abdel-Basset et al. (2021)	Egyptian commercial banks	PF-AHP	PF-TOPSIS, PF-VIKOR, and PF-COPRAS	Multidimensional performance measurement
Gupta et al. (2021a)	Indian commercial banks	CRITIC	TOPSIS	Financial performance assessment
Gupta et al. (2021b)	Indian commercial banks	AHP	interval-valued TOPSIS	Financial performance evaluation
Ecer and Pamucar (2022)	Turkish commercial banks	LOPCOW	DOBI	Sustainability performance measurement
Ünlü et al. (2022)	Turkish commercial banks	SWARA II and MEREC	MARCOS	Analysis of productivity and efficiency performance
Ünlü and Yalçın (2023)	Turkish commercial banks	CRITIC	WASPAS	Financial performance evaluation
Akbulut (2024)	Turkish deposit banks	G-LOPCOW	G-PIV	Analysis of environmental sustainability performance
Akbulut and Aydın (2024)	Turkish deposit banks	MSD and MPSI	RAWEC	Multidimensional performance measurement
Trung et al. (2024)	Vietnamese banks	Equal weights	SRP, PSI, and RAM	Financial performance evaluation
Goel et al. (2024)	Indian banks	Equal weights	GRA	Sustainability performance measurement
Hussain et al. (2024)	Emerging markets banks (China, Pakistan, India, and Thailand)	AHP	TOPSIS and GRA	Financial performance assessment
Ünlü and Çıtak (2025)	Turkish deposit banks	MEREC, CILOS, and CCSD	WASPAS and ARAS	Sustainability performance measurement
Iřık et al. (2025a)	Turkish participation banks	SF-SPC and SF-SWARA	SF-AROMAN	Evaluating sustainability, efficiency, and productivity

Table 1. Continued

Işık et al. (2025b)	Turkish deposit banks	G-SPC and G-MSD	G-SRP	ESG performance comparison
Işık et al. (2025c)	Pakistani commercial banks	F-LBWA and F-LMAW	MARCOS	Analysis of the performance of service network, market performance, and financial health
Karki et al. (2025)	Indian deposit banks	R-SWARA	CoCoSo	ESG performance assessment
Durmuş et al. (2025)	Commercial banks operating in the Balkans	Type-2 NF-PSI	Type-2 NF-CODAS	Financial performance evaluation
Yang et al. (2025)	Chinese commercial banks	ISF method	ISF-TOPSIS	Operational performance evaluation
Peci et al. (2025)	Albanian banks	F-AHP	F-TOPSIS	Financial performance assessment
Karadağ Ak et al. (2025)	Turkish development and investment banks	Entropy	ARAS	Financial performance assessment

As summarized in Table 1, recent studies have employed a diverse range of hybrid MCDM techniques to evaluate bank performance across financial, operational, and sustainability dimensions. These models reflect growing methodological sophistication, incorporating traditional methods, fuzzy logic, and interval-valued data to enhance decision transparency and benchmarking accuracy.

However, a critical conceptual gap remains in the ESG-focused literature. Prior papers have largely treated ESG indicators as isolated metrics, without systematically linking them to underlying sustainability theories. In particular, the theoretical foundations—such as stakeholder theory, legitimacy theory, stewardship theory, and the resource-based view—have not been explicitly mapped to the ESG criteria used in performance evaluation. This omission limits the interpretability and strategic relevance of existing models, especially in regulatory and institutional contexts where ESG disclosure is increasingly mandated.

The present manuscript addresses this gap by integrating ten ESG sustainability criteria across ESG dimensions with four complementary theoretical anchors. Each criterion is conceptually aligned with one or more theories, as detailed in Table 3.

By embedding these theoretical linkages into the analytical structure, the proposed grey-based MCDM framework offers not only methodological novelty but also conceptual depth. It enables a more meaningful interpretation of ESG performance, grounded in institutional accountability, stakeholder legitimacy, and strategic resource utilization. This dual contribution—bridging theory and method—positions the model as a robust decision-support tool for sustainability evaluation in banking.

3. Methodology

This research assesses the ESG performance of publicly listed Turkish banks using an integrated grey-based MCDM framework. The analytical structure combines G-LOPCOW, G-MSD, and G-PIV to ensure methodological diversity and enhance decision robustness under

epistemic uncertainty. Figure 1 presents the schematic flow of the proposed model, while the following section outlines the theoretical foundations of each grey-oriented component.

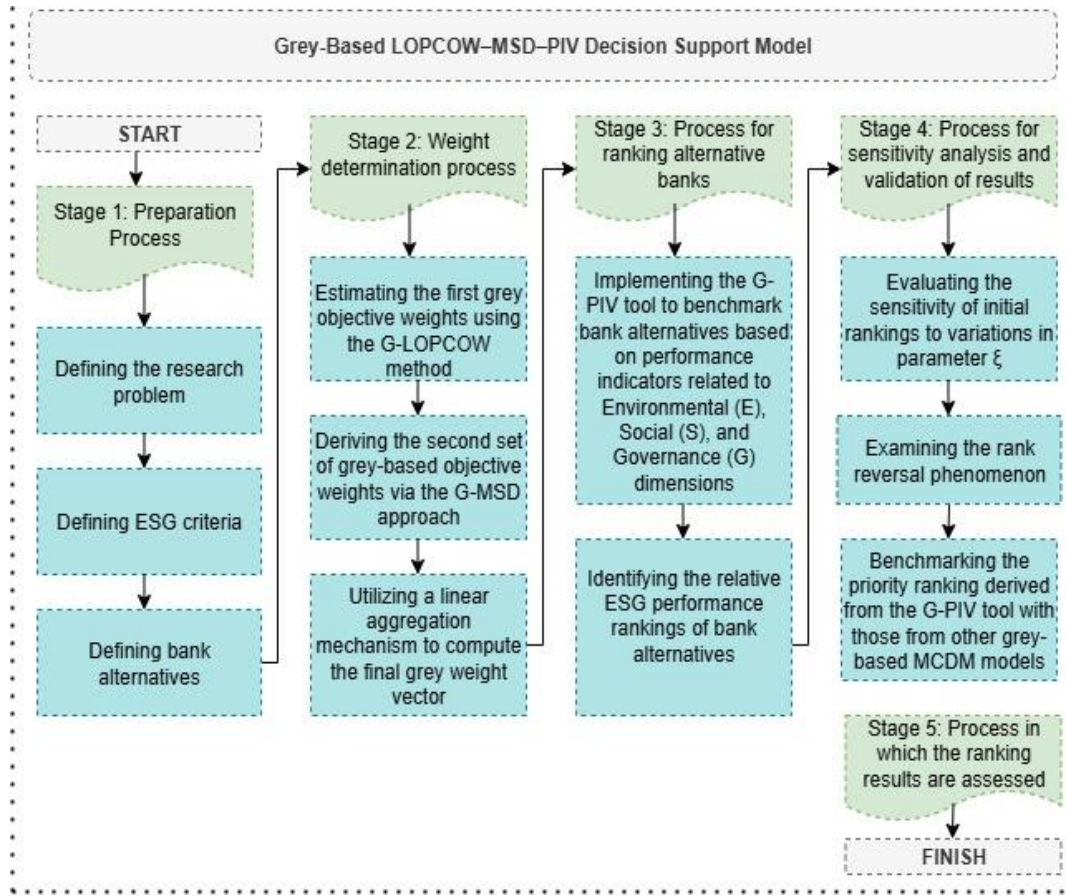


Figure 1. Methodological Framework

3.1. Grey LOPCOW (G-LOPCOW) Methodology

The classical LOPCOW weighting algorithm was originally introduced by Ecer and Pamucar (2022) as a computationally efficient and interpretable method for objective criterion weighting. From a methodological standpoint, it has gained considerable attention across various decision-making domains due to its ability to handle negative data and its straightforward implementation. As an extension of the original model, Ulutař et al. (2024) subsequently developed a grey interval-based version, referred to as G-LOPCOW, to enhance its applicability under uncertainty and incomplete information. This enhancement allows the technique to more effectively address epistemic uncertainty by integrating grey numbers into the weighting process. As a result, its applicability is significantly improved in decision-making environments characterized by incomplete or ambiguous information. The computational framework of the G-LOPCOW procedure is structured as follows:

Step 1. The grey decision matrix $\otimes A$, comprising the set of alternatives and evaluation criteria, is constructed. This matrix is provided in Eq. (1).

$$\otimes A = [\otimes a_{ij}]_{m \times n} = \begin{bmatrix} [a_{11}^l, a_{11}^u] & [a_{12}^l, a_{12}^u] & \cdots & [a_{1n}^l, a_{1n}^u] \\ [a_{21}^l, a_{21}^u] & [a_{22}^l, a_{22}^u] & \cdots & [a_{2n}^l, a_{2n}^u] \\ \vdots & \vdots & \ddots & \vdots \\ [a_{m1}^l, a_{m1}^u] & [a_{m2}^l, a_{m2}^u] & \cdots & [a_{mn}^l, a_{mn}^u] \end{bmatrix}_{m \times n} \quad (1)$$

In Eq. (1), $\otimes a_{ij}$, defined as $\otimes a_{ij} = [a_{ij}^l, a_{ij}^u]$, represents the grey performance value of the i th alternative with respect to the j th assessment criterion. Here, a_{ij}^l and a_{ij}^u denote the lower and upper bounds of the grey interval, respectively.

Step 2. The grey decision matrix presented in Eq. (1) is normalized employing Eq. (2) for beneficial criteria and Eq. (3) for non-beneficial criteria.

$$\otimes b_{ij} = \frac{\otimes a_{ij} - \min\{\otimes a_{ij} | 1 \leq i \leq m\}}{\max\{\otimes a_{ij} | 1 \leq i \leq m\} - \min\{\otimes a_{ij} | 1 \leq i \leq m\}} \quad (2)$$

$$\otimes b_{ij} = \frac{\max\{\otimes a_{ij} | 1 \leq i \leq m\} - \otimes a_{ij}}{\max\{\otimes a_{ij} | 1 \leq i \leq m\} - \min\{\otimes a_{ij} | 1 \leq i \leq m\}} \quad (3)$$

Step 3. The grey percentage values PV_j corresponding to each criterion are computed according to the following formulation.

$$\otimes PV_j = [PV_j^l, PV_j^u] = \left[\ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m (b_{ij}^l)^2}{m}}}{\sigma_j^l} \right) \times 100, \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^m (b_{ij}^u)^2}{m}}}{\sigma_j^u} \right) \times 100 \right] \quad (4)$$

In Equation (4), σ_j^l and σ_j^u denote the lower and upper bounds of the standard deviation scores corresponding to each assessment criterion.

Step 4. The final step of the G-LOPCOW weighting procedure entails the computation of grey weight scores for the selected criteria using Eq. (5)

$$\otimes w_{j,lop} = [w_{j,lop}^l, w_{j,lop}^u] = \left[\min \left(\frac{PV_j^l}{\sum_{j=1}^n PV_j^l}, \frac{PV_j^u}{\sum_{j=1}^n PV_j^u} \right), \max \left(\frac{PV_j^l}{\sum_{j=1}^n PV_j^l}, \frac{PV_j^u}{\sum_{j=1}^n PV_j^u} \right) \right] \quad (5)$$

3.2. Grey Modified Standard Deviation (G-MSD) Procedure

The Standard Deviation (SD) technique, originally recommended by Diakoulaki et al. (1995), has been widely employed in MCDM to derive objective coefficient weights by capturing the dispersion of criterion values across alternatives. To enhance its sensitivity to data magnitude, Puška et al. (2022) introduced the MSD variant, which incorporates two additional steps: computing the column-wise totals and adjusting the standard deviation accordingly. More recently, Işık et al. (2025b) extended this structure into the grey environment by developing the G-MSD model, which integrates grey interval numbers to better handle epistemic uncertainty and incomplete information. This methodological progression reflects a shift toward more robust and uncertainty-resilient weighting procedures in complex decision-making contexts. The implementation of the G-MSD weighting procedure comprises the following steps:

Step 1. The initial grey decision matrix is constructed as shown in Eq. (1).

Step 2. As specified in Eq. (1), the initial grey decision matrix is subjected to normalization, where Eq. (6) is applied to benefit-type criteria and Eq. (7) to cost-type criteria.

$$\otimes b_{ij} = \begin{cases} \otimes b_{ij}^+ = \frac{\otimes b_{ij}}{\max\{\otimes b_{ij} | 1 \leq i \leq m\}} = \left[\frac{b_{ij}^l}{\max\{b_{ij}^l | 1 \leq i \leq m\}}, \frac{b_{ij}^u}{\max\{b_{ij}^u | 1 \leq i \leq m\}} \right] & (6) \\ \otimes b_{ij}^- = \frac{\min\{\otimes b_{ij} | 1 \leq i \leq m\}}{\otimes b_{ij}} = \left[\frac{\min\{b_{ij}^l | 1 \leq i \leq m\}}{(b_{ij}^l)}, \frac{\min\{b_{ij}^u | 1 \leq i \leq m\}}{(b_{ij}^u)} \right] & (7) \end{cases}$$

Step 3. The modified values of the standard deviation scores for each performance measure are obtained through Eq. (8).

$$\otimes t_j = [t_j^l, t_j^u] = \left[\min\left(\frac{\sigma^l}{\sum_{i=1}^m (b_{ij}^l)}\right), \left(\frac{\sigma^u}{\sum_{i=1}^m (b_{ij}^u)}\right), \max\left(\frac{\sigma^l}{\sum_{i=1}^m (b_{ij}^l)}\right), \left(\frac{\sigma^u}{\sum_{i=1}^m (b_{ij}^u)}\right) \right] \quad (8)$$

Step 4. The last phase of the MSD-G procedure involves computing the objective significance weights of each performance criterion using Eq. (9).

$$\otimes w_{j,msd} = [w_{j,msd}^l, w_{j,msd}^u] = \left[\frac{\otimes t_j}{\sum_{j=1}^n \otimes t_j} \left[\min\left(\frac{t_j^l}{\sum_{j=1}^n (t_j^l)}, \frac{t_j^u}{\sum_{j=1}^n (t_j^u)}\right), \max\left(\frac{t_j^l}{\sum_{j=1}^n (t_j^l)}, \frac{t_j^u}{\sum_{j=1}^n (t_j^u)}\right) \right] \right] \quad (9)$$

3.3. Aggregation of Criterion Weights

In MCDM, employing diverse weighting techniques often yields slight variations in the computed criterion weights owing to the inherent differences in their evaluative mechanisms. To reconcile these discrepancies and leverage the complementary strengths of each tool, a linear aggregation operator was utilized to integrate the outputs of the G-LOPCOW and G-MSD procedures. This integration enables a more balanced and epistemically resilient weighting structure. The resulting composite weights offer enhanced interpretability, methodological neutrality, and improved robustness in performance assessment. By synthesizing multiple weighting schemes, the final weights more accurately reflect the relative significance of criteria across uncertain decision environments, thereby strengthening the reliability and analytical depth of the overall assessment. The combined weights are computed employing the following linear integration formula.

$$\otimes w_{j,com} = [w_{j,com}^l, w_{j,com}^u] = [\xi \otimes w_{j,lop} + (1 - \xi) \otimes w_{j,msd}] = [\min(\xi w_{j,lop}^l + (1 - \xi) w_{j,msd}^l), \max(\xi w_{j,lop}^u + (1 - \xi) w_{j,msd}^u)] \quad (10)$$

Here, $w_{j,com}$ ($j = 1, 2, \dots, n$) represents the integrated weight coefficient corresponding to the j^{th} ESG criterion. In the current manuscript, the individual weight coefficients of criteria derived from G-LOPCOW and G-MSD are represented as $\otimes w_{j,lop}$ and $\otimes w_{j,msd}$, respectively. In Eq. (10), the parameter $\xi \in [0, 1]$ denotes the proportional coefficient employed to balance the contribution of individual weighting approaches in the aggregation process. For the initial solution, its value was set to 0.5, implying equal influence from both G-MSD and G-LOPCOW-derived weights. Hence, the applicability and consistency of the proposed aggregation strategy can be empirically validated in different settings.

3.4. Grey PIV Method

The Proximity Indexed Value (PIV) technique, developed by Mufazzal and Muzakkir (2018), is a ranking-oriented MCDM tool designed to minimize the rank reversal phenomenon commonly observed in traditional models. Next, to extend its applicability under uncertainty, Ulutaş et al. (2021) introduced the Grey PIV (G-PIV) approach, which integrates grey system theory into the original PIV structure. G-PIV replaces crisp performance values with grey interval numbers, allowing the technique to handle epistemic uncertainty and incomplete information more effectively. The procedural implementation of the G-PIV consists of five systematic steps.

Step 1. The initial grey decision matrix is formulated in accordance with Eq. (1).

Step 2. Normalization of the values in the initial grey decision matrix is performed via Eq. (11).

$$\otimes k_{ij} = [k_{ij}^l, k_{ij}^u] = \frac{\otimes a_{ij}}{\sqrt{\sum_{i=1}^m (\otimes a_{ij})^2}} = \left[\frac{a_{ij}^l}{\sqrt{\sum_{i=1}^m (a_{ij}^u)^2 + \sum_{i=1}^m (a_{ij}^l)^2}}, \frac{a_{ij}^u}{\sqrt{\sum_{i=1}^m (a_{ij}^u)^2 + \sum_{i=1}^m (a_{ij}^l)^2}} \right] \quad (11)$$

Step 3. The values of the weighted normalized grey decision matrix are obtained by applying Eq. (12).

$$\otimes z_{ij} = [z_{ij}^l, z_{ij}^u] = \otimes w_{j,com} \times \otimes k_{ij} = [w_{j,com}^l \times k_{ij}^l, w_{j,com}^u \times k_{ij}^u] \quad (12)$$

Step 4. The grey weighted proximity index ($\otimes f_{ij} = [f_{ij}^l, f_{ij}^u]$) is obtained for benefit-type criteria using Eq. (13) and for cost-type criteria using Eq. (14).

$$\otimes f_{ij} = \max(\otimes z_{ij}) - \otimes z_{ij} = [\max(z_{ij}^l) - z_{ij}^u, \max(z_{ij}^u) - z_{ij}^l] \quad (13)$$

$$\otimes f_{ij} = \otimes z_{ij} - \min(\otimes z_{ij}) = [z_{ij}^l - \min(z_{ij}^u), z_{ij}^u - \min(z_{ij}^l)] \quad (14)$$

Step 5. In the final step of the G-PIV procedure, the overall proximity values—grey ($\otimes v_i = [v_i^l, v_i^u]$) and crisp v_i —are computed by applying Eqs. (15) and (16), respectively.

$$\otimes v_i = [v_i^l, v_i^u] = \sum_{j=1}^n \otimes f_{ij} = \left[\sum_{j=1}^n f_{ij}^l, \sum_{j=1}^n f_{ij}^u \right] \quad (15)$$

$$v_i = \frac{d_i^l + d_i^u}{2} \quad (16)$$

3.5. Rationale for Choosing the LOPCOW-MSD-PIV Hybrid Combination in Grey Environment and Its Advantages Over Alternative MCDM Frameworks

The selection of the G-LOPCOW–G-MSD–G-PIV combination is driven by both theoretical coherence and practical suitability to the complex data structure underlying ESG performance assessment in the banking industry. ESG assessment demands a methodological framework capable of accommodating epistemic uncertainty, indicator heterogeneity, and incomplete disclosure—characteristics that frequently define sustainability-related datasets. Conventional deterministic MCDM techniques (e.g., Entropy, CRITIC, CRISUS, MEREC, TOPSIS, VIKOR, WASPAS) presuppose complete and precise data, a condition rarely satisfied in ESG reporting. Likewise, although fuzzy-based MCDM models (such as F-AHP, F-BWM, F-TOPSIS, or F-MARCOS) can address linguistic vagueness, they rely extensively on expert

elicitation for defining membership functions and constructing pairwise comparison matrices. This dependence on subjective judgment may introduce cognitive bias and reduce reproducibility—an especially critical limitation in regulated sectors such as banking, where methodological transparency and data objectivity are paramount.

In contrast, the present study employs a fully data-driven grey-based hybrid framework that unites three complementary models within a unified theoretical structure. The weighting phase integrates G-LOPCOW and G-MSD, which collectively capture both information sensitivity and dispersion-based variability through objective statistical computation. G-LOPCOW, through its logarithmic mechanism, measures the proportional responsiveness of each criterion to marginal performance changes within grey intervals, thereby detecting subtle ESG performance differences across banks. G-MSD, in turn, quantifies the magnitude of dispersion and asymmetry within these intervals, accurately representing volatility in sustainability outcomes. The linear aggregation of these two tools creates a dual-objective weighting equilibrium between sensitivity and stability, generating weight vectors that are statistically coherent and free from expert bias.

The ranking stage, conducted through G-PIV, complements this weighting design by offering a transparent, rank-reversal-resistant decision procedure. Unlike conventional distance-based methods, G-PIV employs a proximity indexing logic that preserves ranking consistency under interval-valued data and avoids distortions arising from deterministic normalization. Its analytical robustness makes it particularly effective for ESG applications, where the indicators—often drawn from third-party databases such as Refinitiv Eikon or Bloomberg ESG—are inherently incomplete or partially disclosed. The G-PIV's simplicity and interpretability further enhance its value to finance practitioners, risk managers, and regulatory stakeholders who need reliable sustainability rankings without resorting to subjective expert opinions.

Compared with fuzzy-based or expert-dependent grey MCDM approaches, the proposed grey-based framework is entirely empirical and evidence-driven. All parameters are derived directly from observed data, ensuring methodological neutrality and compliance with the evidence-based evaluation principles increasingly emphasized by financial regulators and sustainable-finance institutions. This structure minimizes cognitive subjectivity, enhances reproducibility over time, and ensures that the assessment remains stable even as new ESG data emerge.

From an epistemological perspective, integrating G-LOPCOW, G-MSD, and G-PIV yields a mathematically robust and uncertainty-resilient decision-support system tailored for decision makers and practitioners in the banking industry. All three components operate within the same grey-system logic, ensuring internal consistency throughout the weighting and ranking stages. Consequently, the Grey LOPCOW–MSD–PIV hybrid method provides a unified, transparent, and replicable analytical environment that is empirically rigorous, statistically robust, and conceptually aligned with the uncertainty-laden structure of ESG performance assessment in modern banking.

4. Data Set and Sample

The empirical analysis employs a dataset specifically designed to assess the sustainability performance of Turkish publicly listed banks through a novel grey-based hybrid method. The recommended model integrates epistemic uncertainty into the ESG evaluation process, ensuring

a robust and comprehensive comparison of institutional sustainability capacities across the domestic banking industry.

A total of nine commercial banks listed on BIST constitute the decision alternatives under investigation. These banks were chosen based on the availability of consistent ESG data over the 2021–2023 period, ensuring comparability and data reliability. The corresponding codes and rankings of the bank alternatives are presented in Table 2. The assessment framework rests upon a three-dimensional ESG structure, comprising ten measurable indicators that collectively capture the ESG pillars of sustainability. As detailed in Table 3, the environmental dimension (E1–E3) encompasses resource use, emissions management, and environmental innovation, reflecting the extent to which banks utilize their tangible and intangible resources to achieve environmental efficiency. The social dimension (S1–S4) covers workforce management, human rights practices, community engagement, and product responsibility, which jointly express how financial institutions align their social policies with stakeholder expectations and ethical standards. Finally, the governance dimension (G1–G3) integrates management effectiveness, shareholder relations, and corporate social responsibility (CSR) performance, representing the internal governance quality and strategic commitment to long-term value creation. Each of the ten ESG indicators was formulated under the maximization criterion, indicating that higher scores correspond to superior sustainability performance. This optimization direction aligns with the MCDM principle of utility maximization, wherein greater values reflect improved environmental efficiency, stronger social responsibility, and more transparent governance structures.

Furthermore, the inclusion of theoretical linkages for each ESG criterion ensures conceptual validity and interpretive depth. Specifically, the Resource-Based View (RBV) underpins indicators related to environmental innovation and resource efficiency, positioning sustainability-oriented capabilities as strategic assets. The Stakeholder Theory provides the foundation for criteria emphasizing social and relational responsibilities, such as community engagement and shareholder relations. The Stewardship Theory justifies management- and workforce-related criteria by emphasizing long-term institutional commitment and ethical leadership. Finally, the Legitimacy Theory explains indicators like emissions control, human rights, and CSR by framing sustainability as a mechanism to maintain social acceptance and regulatory conformity. In this context, the selected ESG criteria are not arbitrary performance measures but represent theoretically grounded constructs that collectively portray the multidimensional sustainability posture of the Turkish banking sector. Their maximization ensures that the proposed grey-based hybrid MCDM model effectively captures the most desirable outcomes across all ESG fronts.

Table 2. Bank Alternatives

Rank	Firm	Code
1	Akbank	A1
2	Garanti	A2
3	Vakıfbank	A3
4	Halkbank	A4
5	İşbank	A5
6	Yapı Kredi	A6
7	Albaraka	A7
8	Şekerbank	A8
9	Türkiye Sınai Kalkınma Bankası (TSKB)	A9

Table 3. ESG Sustainability Indicators

Dimension	Assessment Criteria	Code	Relevant Theory
Environmental Performance Indicators	Resource Use	E1	Recourse-Based Theory
	Emissions	E2	Legitimacy Theory
	Innovation	E3	Recourse-Based Theory/ Stakeholder Theory
Social Performance Indicators	Workforce	S1	Stewardship Theory
	Human Rights	S2	Legitimacy Theory/ Stakeholder Theory
	Community	S3	Stakeholder Theory
	Product Responsibility	S4	Stewardship Theory/ Legitimacy Theory
Governance Performance Indicators	Management	G1	Stewardship Theory
	Shareholders	G2	Legitimacy Theory/ Stakeholder Theory
	Corporate Social Responsibility	G3	Legitimacy Theory/ Recourse-Based Theory

5. Application Outcomes

This section outlines the empirical outcomes of the grey-based decision model developed for assessing the multidimensional ESG sustainability performance of nine banks traded on BIST. To implement the three grey-based models, the required ESG data were retrieved from the Refinitiv Eikon database. The dataset covers the period from 2021 to 2023. For each technique, the initial grey decision matrix was constructed after the minimum and maximum values for every criterion were determined across the three-year span. These values define the lower and upper bounds of the grey numbers, respectively. Table 4 presents the resulting matrix structure.

5.1. Empirical Findings of G-LOPCOW Algorithm

As outlined earlier, the first phase of the G-LOPCOW algorithm entails the construction of the grey initial decision matrix. As presented in Table 4, the smallest value in this grey matrix defines the lower bound of the corresponding grey number, whereas the largest value determines its upper bound.

Table 4. Initial Grey Decision Matrix

	E1	E2	E3	S1	S2
A1	[89.54, 93.14]	[91.14, 99.60]	[66.80, 81.76]	[82.07, 90.39]	[51.75, 55.50]
A2	[92.03, 97.55]	[98.53, 98.84]	[79.40, 97.54]	[81.42, 96.87]	[95.45, 96.68]
A3	[80.44, 98.56]	[97.76, 98.70]	[96.48, 96.80]	[84.69, 86.54]	[95.45, 95.70]
A4	[80.13, 85.66]	[80.95, 91.35]	[49.46, 55.33]	[82.45, 90.96]	[78.76, 80.13]
A5	[97.60, 99.85]	[99.19, 99.60]	[96.48, 97.54]	[98.68, 99.58]	[95.45, 96.17]
A6	[67.72, 70.92]	[66.46, 71.56]	[49.46, 60.45]	[73.49, 74.58]	[56.59, 96.54]
A7	[47.35, 80.52]	[74.87, 99.25]	[96.48, 97.14]	[98.10, 99.02]	[78.76, 79.69]
A8	[91.46, 96.77]	[94.58, 95.97]	[49.46, 55.78]	[94.99, 96.45]	[95.45, 96.47]
A9	[90.25, 94.34]	[82.92, 97.64]	[90.38, 91.09]	[89.01, 95.55]	[95.45, 96.25]

Table 4. Continued

	S3	S4	G1	G2	G3
A1	[40.22, 51.15]	[87.56, 90.46]	[34.66, 43.25]	[43.63, 48.30]	[81.38, 90.24]
A2	[88.55, 91.66]	[96.40, 98.55]	[25.57, 76.81]	[60.78, 71.59]	[96.28, 97.57]
A3	[98.08, 98.68]	[96.40, 98.11]	[46.02, 51.66]	[84.66, 89.69]	[56.91, 82.93]
A4	[88.90, 99.48]	[98.11, 99.20]	[44.61, 51.70]	[25.98, 34.66]	[56.91, 58.54]
A5	[98.87, 99.14]	[99.57, 99.80]	[42.56, 82.39]	[60.78, 71.59]	[80.58, 82.93]
A6	[23.88, 27.15]	[60.56, 63.67]	[30.11, 35.44]	[53.43, 66.48]	[68.90, 83.14]
A7	[83.72, 85.72]	[96.40, 98.25]	[62.25, 67.61]	[34.80, 40.34]	[80.52, 82.93]
A8	[99.39, 99.83]	[96.40, 98.96]	[28.92, 33.52]	[35.80, 78.85]	[90.43, 96.95]
A9	[89.93, 95.55]	[29.63, 79.15]	[47.16, 48.85]	[76.58, 82.39]	[58.54, 83.44]

Since the ten ESG criteria included in the initial grey decision matrix are benefit-oriented, normalization was performed with the help of Eq. (2). The resulting normalized grey matrix is presented in Table 5.

Table 5. Grey-Based Normalized Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.80, 0.87]	[0.74, 1.00]	[0.36, 0.67]	[0.33, 0.65]	[0.00, 0.08]
A2	[0.85, 0.96]	[0.97, 0.98]	[0.62, 1.00]	[0.30, 0.90]	[0.97, 1.00]
A3	[0.63, 0.98]	[0.94, 0.97]	[0.98, 0.98]	[0.43, 0.50]	[0.97, 0.98]
A4	[0.62, 0.73]	[0.44, 0.75]	[0.00, 0.12]	[0.34, 0.67]	[0.60, 0.63]
A5	[0.96, 1.00]	[0.99, 1.00]	[0.98, 1.00]	[0.97, 1.00]	[0.97, 0.99]
A6	[0.39, 0.45]	[0.00, 0.15]	[0.00, 0.23]	[0.00, 0.04]	[0.11, 1.00]
A7	[0.00, 0.63]	[0.25, 0.99]	[0.98, 0.99]	[0.94, 0.98]	[0.60, 0.62]
A8	[0.84, 0.94]	[0.85, 0.89]	[0.00, 0.13]	[0.82, 0.88]	[0.97, 1.00]
A9	[0.82, 0.90]	[0.50, 0.94]	[0.85, 0.87]	[0.59, 0.85]	[0.97, 0.99]
	S3	S4	G1	G2	G3
A1	[0.22, 0.36]	[0.83, 0.87]	[0.16, 0.31]	[0.28, 0.35]	[0.60, 0.82]
A2	[0.85, 0.89]	[0.95, 0.98]	[0.00, 0.90]	[0.55, 0.72]	[0.97, 1.00]
A3	[0.98, 0.98]	[0.95, 0.98]	[0.36, 0.46]	[0.92, 1.00]	[0.00, 0.64]
A4	[0.86, 1.00]	[0.98, 0.99]	[0.34, 0.46]	[0.00, 0.14]	[0.00, 0.04]
A5	[0.99, 0.99]	[1.00, 1.00]	[0.30, 1.00]	[0.55, 0.72]	[0.58, 0.64]
A6	[0.00, 0.04]	[0.44, 0.49]	[0.08, 0.17]	[0.43, 0.64]	[0.29, 0.65]
A7	[0.79, 0.81]	[0.95, 0.98]	[0.65, 0.74]	[0.14, 0.23]	[0.58, 0.64]
A8	[0.99, 1.00]	[0.95, 0.99]	[0.06, 0.14]	[0.15, 0.83]	[0.82, 0.98]
A9	[0.87, 0.94]	[0.00, 0.71]	[0.38, 0.41]	[0.79, 0.89]	[0.04, 0.65]

At the concluding stage of the analysis, the grey objective weights were derived through the application of Eqs. (4) and (5). As shown in Table 6, the crisp weight of each criterion was computed by taking the arithmetic mean of its lower and upper grey bounds.

Table 6. G-LOPCOW Results

	E1	E2	E3	S1	S2
$\otimes PV_j$	[104.12, 134.24]	[92.68, 95.76]	[53.88, 53.90]	[70.16, 85.21]	[78.80, 90.61]
$\otimes w_{j,lop}$	[0.139, 0.147]	[0.105, 0.124]	[0.059, 0.072]	[0.093, 0.094]	[0.099, 0.105]
$w_{j,lop}$	0.143	0.114	0.066	0.094	0.102
Rank	2	3	10	6	5
	S3	S4	G1	G2	G3
$\otimes PV_j$	[84.74, 84.98]	[97.33, 155.81]	[45.71, 64.94]	[52.60, 77.67]	[67.63, 68.69]
$\otimes w_{j,lop}$	[0.093, 0.113]	[0.130, 0.171]	[0.061, 0.071]	[0.070, 0.085]	[0.075, 0.090]
$w_{j,lop}$	0.103	0.151	0.066	0.078	0.083
Rank	4	1	9	8	7

5.2. Empirical Findings Based on the G-MSD Algorithm

In this section, the second set of objective importance weights—based on grey numbers—is computed via the G-MSD procedure. To initiate the process, the initial grey decision matrix—presented in Table 4—is constructed. Subsequently, each element in the matrix is normalized via Eq. (6), taking into account the nature of the corresponding criterion. The resulting normalized grey decision matrix is reported in Table 7. Next, Table 8 summarizes the final results of the G-MSD procedure, which were computed based on Eqs. (8) and (9). As illustrated in Table 8, the crisp weight of each criterion was obtained by calculating the arithmetic mean of its corresponding lower and upper grey bounds.

Table 7. Grey-Based Normalized Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.90, 0.93]	[0.92, 1.00]	[0.68, 0.84]	[0.82, 0.91]	[0.54, 0.57]
A2	[0.92, 0.98]	[0.99, 0.99]	[0.81, 1.00]	[0.82, 0.97]	[0.99, 1.00]
A3	[0.81, 0.99]	[0.98, 0.99]	[0.99, 0.99]	[0.85, 0.87]	[0.99, 0.99]
A4	[0.80, 0.86]	[0.81, 0.92]	[0.51, 0.57]	[0.83, 0.91]	[0.81, 0.83]
A5	[0.98, 1.00]	[1.00, 1.00]	[0.99, 1.00]	[0.99, 1.00]	[0.99, 0.99]
A6	[0.68, 0.71]	[0.67, 0.72]	[0.51, 0.62]	[0.74, 0.75]	[0.59, 1.00]
A7	[0.47, 0.81]	[0.75, 1.00]	[0.99, 1.00]	[0.99, 0.99]	[0.81, 0.82]
A8	[0.92, 0.97]	[0.95, 0.96]	[0.51, 0.57]	[0.95, 0.97]	[0.99, 1.00]
A9	[0.90, 0.94]	[0.83, 0.98]	[0.93, 0.93]	[0.89, 0.96]	[0.99, 1.00]
	S3	S4	G1	G2	G3
A1	[0.40, 0.51]	[0.88, 0.91]	[0.42, 0.52]	[0.49, 0.54]	[0.83, 0.92]
A2	[0.89, 0.92]	[0.97, 0.99]	[0.31, 0.93]	[0.68, 0.80]	[0.99, 1.00]
A3	[0.98, 0.99]	[0.97, 0.98]	[0.56, 0.63]	[0.94, 1.00]	[0.58, 0.85]
A4	[0.89, 1.00]	[0.98, 0.99]	[0.54, 0.63]	[0.29, 0.39]	[0.58, 0.60]
A5	[0.99, 0.99]	[1.00, 1.00]	[0.52, 1.00]	[0.68, 0.80]	[0.83, 0.85]
A6	[0.24, 0.27]	[0.61, 0.64]	[0.37, 0.43]	[0.60, 0.74]	[0.71, 0.85]
A7	[0.84, 0.86]	[0.97, 0.98]	[0.76, 0.82]	[0.39, 0.45]	[0.83, 0.85]
A8	[1.00, 1.00]	[0.97, 0.99]	[0.35, 0.41]	[0.40, 0.88]	[0.93, 0.99]
A9	[0.90, 0.96]	[0.30, 0.79]	[0.57, 0.59]	[0.85, 0.92]	[0.60, 0.86]

Table 8. Results of the G-MSD Procedure

	$\sum_{j=1}^n \otimes b_j$	$\otimes \sigma_j$	$\otimes t_j$	$\otimes w_{j,msd}$	$w_{j,msd}$	Rank
E1	[7.38, 8.19]	[0.10, 0.16]	[0.01, 0.02]	[0.06, 0.08]	0.068	8
E2	[7.90, 8.56]	[0.09, 0.12]	[0.01, 0.01]	[0.05, 0.05]	0.053	9
E3	[6.91, 7.52]	[0.19, 0.22]	[0.03, 0.03]	[0.12, 0.13]	0.121	4
S1	[7.88, 8.33]	[0.08, 0.09]	[0.01, 0.01]	[0.04, 0.05]	0.043	10
S2	[7.69, 8.20]	[0.15, 0.18]	[0.02, 0.02]	[0.09, 0.09]	0.087	6
S3	[7.13, 7.50]	[0.26, 0.28]	[0.03, 0.04]	[0.14, 0.17]	0.156	2
S4	[7.63, 8.28]	[0.13, 0.24]	[0.02, 0.03]	[0.07, 0.12]	0.095	5
G1	[4.39, 5.96]	[0.14, 0.21]	[0.03, 0.04]	[0.13, 0.15]	0.143	3
G2	[5.31, 6.51]	[0.22, 0.22]	[0.03, 0.04]	[0.15, 0.16]	0.157	1
G3	[6.87, 7.78]	[0.12, 0.15]	[0.02, 0.02]	[0.07, 0.08]	0.077	7

5.3. Final Results Regarding the Criterion Weight Coefficients

The final step of the weight estimation procedure involves integrating the grey weight values obtained from the G-LOPCOW and G-MSD methods, as formulated in Eq. (10). The resulting combined grey weights are presented in Table 9. These grey weights are subsequently converted into crisp coefficients by computing the arithmetic mean of their respective lower and upper bounds. A detailed analysis of the results in Table 9 indicates that the three most influential determinants of banks’ ESG sustainable performance are Community (S3), Product Responsibility (S4), and Shareholders (G2), respectively.

Table 9. Aggregated Grey Weights

	$\otimes w_{j,lop}$	$\otimes w_{j,msd}$	$\otimes w_{j,com}$	$w_{j,com}$	Rank
E1	[0.139, 0.147]	[0.058, 0.078]	[0.099, 0.113]	[0.106]	4
E2	[0.105, 0.124]	[0.052, 0.055]	[0.078, 0.089]	[0.084]	8
E3	[0.059, 0.072]	[0.117, 0.126]	[0.088, 0.099]	[0.093]	7
S1	[0.093, 0.094]	[0.040, 0.046]	[0.067, 0.070]	[0.068]	10
S2	[0.099, 0.105]	[0.087, 0.087]	[0.093, 0.096]	[0.095]	6
S3	[0.093, 0.113]	[0.142, 0.169]	[0.118, 0.141]	[0.129]	1
S4	[0.130, 0.171]	[0.073, 0.116]	[0.102, 0.143]	[0.123]	2
G1	[0.061, 0.071]	[0.130, 0.155]	[0.096, 0.113]	[0.104]	5
G2	[0.070, 0.085]	[0.153, 0.161]	[0.112, 0.123]	[0.117]	3
G3	[0.075, 0.090]	[0.073, 0.081]	[0.074, 0.086]	[0.080]	9

5.4. Findings from G-PIV Procedure

Following the determination of the final grey-based importance weights for the evaluation criteria, this section advances to the ranking of banks according to their ESG performance through the application of the G-PIV approach. In this regard, the initial grey decision matrix—constructed in accordance with Eq. (1) and presented in Table 4—serves as the analytical foundation. In the subsequent stage of the G-PIV procedure, all elements of the decision matrix were normalized via Eq. (11), yielding the normalized grey decision matrix reported in Table 10. Thereafter, the weighted normalized grey decision matrix—obtained by applying Eq. (12)—is presented in Table 11. The grey weighted proximity index for benefit-type criteria was then obtained based on Eq. (13), and the results are summarized in Table 12. In the final stage of the G-PIV methodology, the overall grey proximity index values—representing the aggregate ESG

performance scores of the evaluated banks—were derived with the aid of Eqs. (15) and (16). The computed grey proximity index values are displayed in Table 13. From Table 13

Table 10. Grey-Based Normalized Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.23, 0.33]	[0.07, 0.68]	[0.06, 0.27]	[0.07, 0.26]	[0.02, 0.16]
A2	[0.13, 0.13]	[0.08, 0.09]	[0.16, 0.32]	[0.09, 0.18]	[0.23, 0.29]
A3	[0.22, 0.28]	[0.06, 0.07]	[0.11, 0.28]	[0.10, 0.32]	[0.22, 0.32]
A4	[0.28, 0.31]	[0.07, 0.07]	[0.20, 0.33]	[0.26, 0.39]	[0.18, 0.27]
A5	[0.16, 0.18]	[0.06, 0.06]	[0.04, 0.24]	[0.03, 0.18]	[0.25, 0.28]
A6	[0.16, 0.20]	[0.06, 0.06]	[0.10, 0.39]	[0.07, 0.33]	[0.18, 0.24]
A7	[0.22, 0.31]	[0.05, 0.06]	[0.09, 0.31]	[0.09, 0.40]	[0.15, 0.35]
A8	[0.23, 0.32]	[0.06, 0.68]	[0.11, 0.34]	[0.12, 0.39]	[0.19, 0.33]
A9	[0.19, 0.22]	[0.06, 0.06]	[0.10, 0.30]	[0.10, 0.27]	[0.15, 0.23]
	S3	S4	G1	G2	G3
A1	[0.23, 0.26]	[0.25, 0.33]	[0.02, 0.12]	[0.15, 0.21]	[0.02, 0.23]
A2	[0.05, 0.08]	[0.08, 0.10]	[0.38, 0.41]	[0.08, 0.12]	[0.07, 0.09]
A3	[0.19, 0.23]	[0.14, 0.23]	[0.16, 0.22]	[0.17, 0.21]	[0.25, 0.26]
A4	[0.15, 0.20]	[0.08, 0.17]	[0.14, 0.16]	[0.11, 0.15]	[0.23, 0.25]
A5	[0.28, 0.38]	[0.19, 0.31]	[0.28, 0.31]	[0.36, 0.45]	[0.28, 0.28]
A6	[0.22, 0.29]	[0.28, 0.39]	[0.24, 0.30]	[0.23, 0.35]	[0.26, 0.27]
A7	[0.16, 0.21]	[0.23, 0.30]	[0.14, 0.21]	[0.11, 0.14]	[0.24, 0.27]
A8	[0.14, 0.25]	[0.13, 0.18]	[0.13, 0.20]	[0.09, 0.22]	[0.24, 0.26]
A9	[0.29, 0.35]	[0.25, 0.30]	[0.21, 0.26]	[0.27, 0.37]	[0.26, 0.27]

Table 11. Weighted Normalized Grey Decision Matrix

	E1	E2	E3	S1	S2
A1	[0.02, 0.04]	[0.01, 0.06]	[0.01, 0.03]	[0.00, 0.02]	[0.00, 0.02]
A2	[0.01, 0.02]	[0.01, 0.01]	[0.01, 0.03]	[0.01, 0.01]	[0.02, 0.03]
A3	[0.02, 0.03]	[0.00, 0.01]	[0.01, 0.03]	[0.01, 0.02]	[0.02, 0.03]
A4	[0.03, 0.03]	[0.01, 0.01]	[0.02, 0.03]	[0.02, 0.03]	[0.02, 0.03]
A5	[0.02, 0.02]	[0.00, 0.01]	[0.00, 0.02]	[0.00, 0.01]	[0.02, 0.03]
A6	[0.02, 0.02]	[0.00, 0.01]	[0.01, 0.04]	[0.00, 0.02]	[0.02, 0.02]
A7	[0.02, 0.04]	[0.00, 0.01]	[0.01, 0.03]	[0.01, 0.03]	[0.01, 0.03]
A8	[0.02, 0.04]	[0.01, 0.06]	[0.01, 0.03]	[0.01, 0.03]	[0.02, 0.03]
A9	[0.02, 0.02]	[0.00, 0.01]	[0.01, 0.03]	[0.01, 0.02]	[0.01, 0.02]
	S3	S4	G1	G2	G3
A1	[0.03, 0.04]	[0.02, 0.05]	[0.00, 0.01]	[0.02, 0.03]	[0.00, 0.02]
A2	[0.01, 0.01]	[0.01, 0.01]	[0.04, 0.05]	[0.01, 0.01]	[0.01, 0.01]
A3	[0.02, 0.03]	[0.01, 0.03]	[0.02, 0.02]	[0.02, 0.03]	[0.02, 0.02]
A4	[0.02, 0.03]	[0.01, 0.02]	[0.01, 0.02]	[0.01, 0.02]	[0.02, 0.02]
A5	[0.03, 0.05]	[0.02, 0.04]	[0.03, 0.03]	[0.04, 0.06]	[0.02, 0.02]
A6	[0.03, 0.04]	[0.03, 0.06]	[0.02, 0.03]	[0.03, 0.04]	[0.02, 0.02]
A7	[0.02, 0.03]	[0.02, 0.04]	[0.01, 0.02]	[0.01, 0.02]	[0.02, 0.02]
A8	[0.02, 0.04]	[0.01, 0.03]	[0.01, 0.02]	[0.01, 0.03]	[0.02, 0.02]
A9	[0.03, 0.05]	[0.03, 0.04]	[0.02, 0.03]	[0.03, 0.05]	[0.02, 0.02]

Table 12. Grey Weighted Proximity Index Matrix

	E1	E2	E3	S1	S2
A1	[-0.01, 0.02]	[-0.05, 0.06]	[-0.01, 0.03]	[0.00, 0.02]	[0.01, 0.03]
A2	[0.01, 0.03]	[0.00, 0.05]	[-0.01, 0.02]	[0.00, 0.02]	[0.00, 0.01]
A3	[0.00, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[-0.01, 0.02]	[-0.01, 0.01]
A4	[-0.01, 0.01]	[0.00, 0.06]	[-0.01, 0.02]	[-0.01, 0.01]	[0.00, 0.02]
A5	[0.01, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[0.00, 0.03]	[0.00, 0.01]
A6	[0.00, 0.02]	[0.00, 0.06]	[-0.02, 0.03]	[-0.01, 0.02]	[0.00, 0.02]
A7	[-0.01, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[-0.01, 0.02]	[-0.01, 0.02]
A8	[-0.01, 0.01]	[-0.05, 0.06]	[-0.02, 0.03]	[-0.01, 0.02]	[-0.01, 0.02]
A9	[0.00, 0.02]	[0.00, 0.06]	[-0.01, 0.03]	[0.00, 0.02]	[-0.02, 0.02]
	S3	S4	G1	G2	G3
A1	[0.00, 0.03]	[-0.02, 0.03]	[0.02, 0.04]	[0.01, 0.04]	[0.00, 0.02]
A2	[0.02, 0.05]	[0.01, 0.05]	[-0.01, 0.01]	[0.02, 0.05]	[0.01, 0.02]
A3	[0.00, 0.03]	[0.00, 0.04]	[0.01, 0.03]	[0.01, 0.04]	[0.00, 0.01]
A4	[0.01, 0.04]	[0.00, 0.05]	[0.02, 0.03]	[0.02, 0.04]	[0.00, 0.01]
A5	[-0.02, 0.02]	[-0.02, 0.04]	[0.00, 0.02]	[-0.02, 0.02]	[0.00, 0.00]
A6	[-0.01, 0.03]	[-0.03, 0.03]	[0.00, 0.02]	[0.00, 0.03]	[0.00, 0.00]
A7	[0.00, 0.04]	[-0.01, 0.03]	[0.01, 0.03]	[0.02, 0.04]	[0.00, 0.01]
A8	[0.00, 0.04]	[0.00, 0.04]	[0.01, 0.03]	[0.01, 0.04]	[0.00, 0.01]
A9	[-0.01, 0.02]	[-0.01, 0.03]	[0.01, 0.03]	[-0.01, 0.02]	[0.00, 0.01]

Table 13. G-PIV-Based ESG Performance Evaluation Results

	$\otimes v_i$	v_i	Rank
A1	[-0.051, 0.323]	0.136	5
A2	[0.063, 0.307]	0.185	9
A3	[-0.005, 0.282]	0.138	6
A4	[0.013, 0.281]	0.147	8
A5	[-0.050, 0.245]	0.098	1
A6	[-0.060, 0.261]	0.100	2
A7	[-0.018, 0.295]	0.138	7
A8	[-0.072, 0.301]	0.114	4
A9	[-0.040, 0.252]	0.106	3

According to the ranking results presented in Table 13, the top three performing banks are A5 (İşbank), A6 (Yapı kredi), and A9 (TSKB). These alternatives exhibit the lowest proximity scores, indicating a strong alignment with the ideal ESG profile and suggesting robust sustainability practices across multiple dimensions. In contrast, the lowest-ranked banks—A2 (Garanti), A4 (Halkbank), and A7 (Albaraka)—demonstrate relatively higher proximity scores, reflecting a greater distance from the ideal benchmark and signaling potential weaknesses in their ESG performance.

6. Robustness and Sensitivity Analyses

In this section, a comprehensive three-stage sensitivity analysis was carried out to assess the reliability, stability, and parametric robustness of the introduced grey-based framework. In the first stage, the ranking results obtained through the G-PIV methodology—based on the integrated weighting of the G-LOPCOW and G-MSD techniques—were compared with those derived from alternative grey MCDM tools. This comparison aimed to assess inter-method consistency and validate the correlative soundness of the proposed model. In the second stage,

the potential occurrence of rank reversal was examined to test the structural stability of the grey decision-making approach. In this context, the effect of varying the number of alternatives on the final rankings was systematically analyzed. Finally, in the third stage, the impact of varying the parameter ξ —employed in determining the final criterion weights—on the resulting bank rankings was analyzed to examine the grey model’s sensitivity to parameter changes.

6.1. Comparative Analysis

In the first stage of the robustness analysis, the reliability and consistency of the ranking results obtained through the proposed G-PIV methodology—based on the integrated weighting of G-LOPCOW and G-MSD—were thoroughly examined. For this purpose, several widely recognized grey-based decision-making approaches from the literature were employed for comparative evaluation, including G-RAWEC (Ulutař et al., 2025), G-SAW (Churchman and Ackoff, 1954), G-MARCOS (Torkayesh et al., 2021), and G-COPRAS (Zavadskas et al., 2008). The findings of these comparisons are illustrated in Figure 2. Notably, no changes were observed in the rankings of alternatives A5, A6, A9, A4, and A2, while only minor shifts were detected in the rankings of the remaining alternatives. These results collectively indicate that the proposed grey hybrid model yields stable and reliable outcomes, reinforcing its methodological soundness and practical applicability in ESG-based decision contexts.

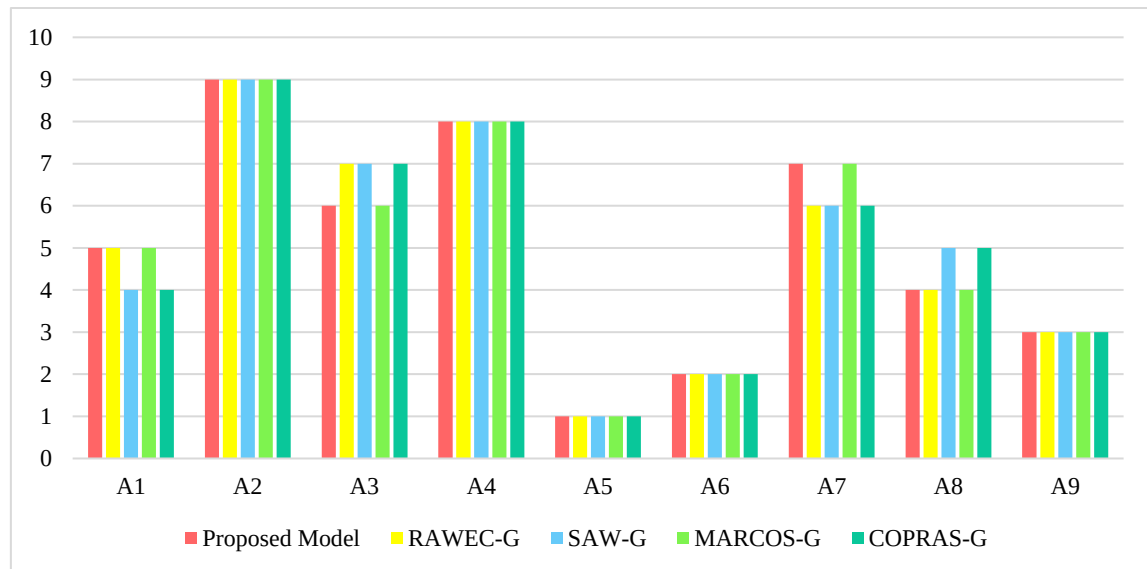


Figure 2. Comparative Rankings Across Grey MCDM Techniques

6.2. Investigation of the Rank Reversal Phenomenon

In the second stage of the robustness analysis, the reliability of the proposed integrated grey decision-making model and the stability of its ranking structure were examined through the lens of the rank reversal phenomenon. In this context, the lowest-performing bank was systematically removed from the analysis in each scenario, and the process was repeated iteratively until only the top-ranked bank remained. The empirical results obtained across nine distinct scenarios are presented in Figure 3. As illustrated, the exclusion of the least-performing alternative in each iteration did not lead to any changes in the final ranking order. This finding clearly demonstrates

that the proposed model exhibits a high degree of robustness and consistency, even under structural modifications to the decision matrix.

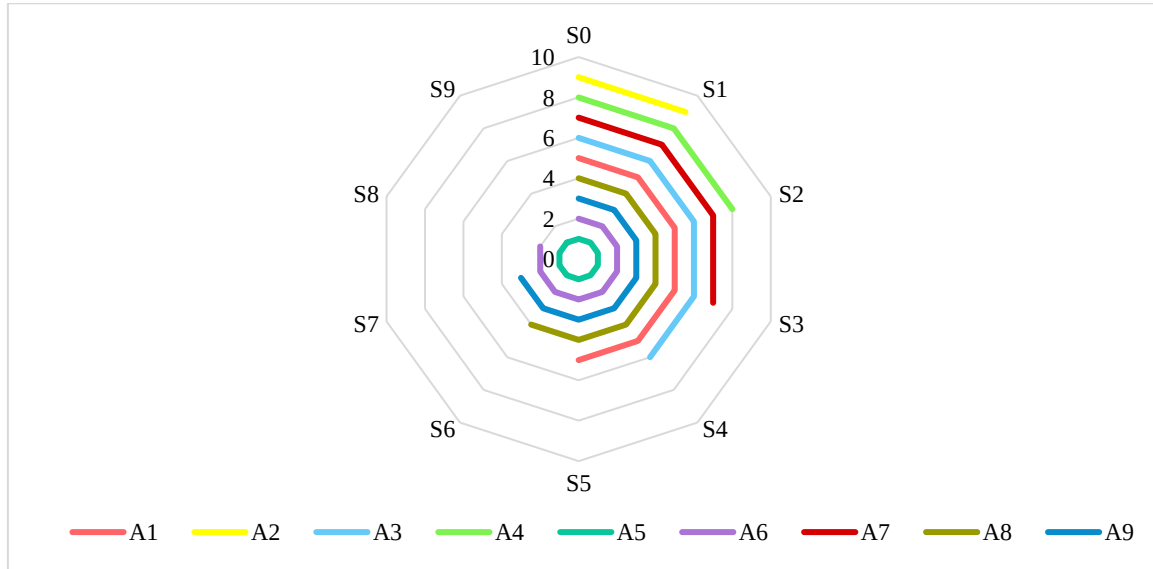


Figure 3. Rankings of Bank Alternatives Across Generated Scenarios

6.3. Parametric Robustness Analysis Based on the Parameter ξ

In the final stage of the robustness analysis, the influence of varying the parameter ξ — utilized in the final weighting process—on the bank rankings was systematically assessed. According to preceding studies in the MCDM literature, the parameter ξ is typically incorporated into calculations employing a fixed value of 0.5. However, ξ has the flexibility to assume different values within the $[0, 1]$ interval. Therefore, the analysis was not limited to the conventional value of 0.5; instead, twenty distinct scenarios were formed by considering incremental ξ values ranging from 0 to 1 (i.e., 0, 0.05, 0.10, ..., 1). The results of these analyses are provided in Figure 4.

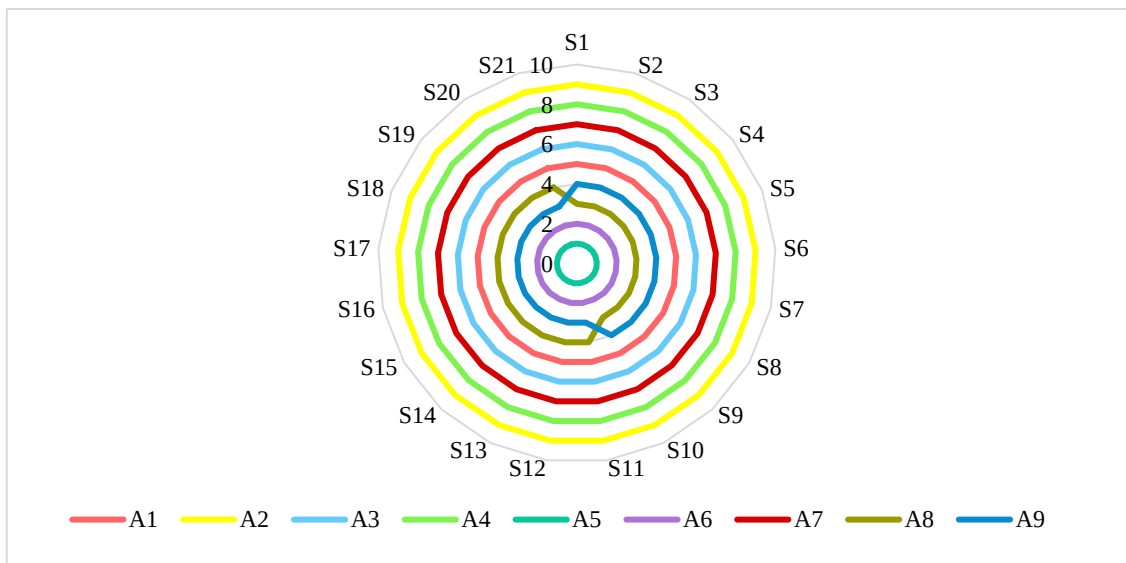


Figure 4. Bank Rankings Under Modified ξ -Based Weighting Scenario

From Figure 4, it is observed that changes in the ξ parameter do not significantly affect the ranking structure of the bank alternatives—except for two specific cases. This finding clearly demonstrates that the proposed grey-based methodological framework exhibits a high degree of stability and consistency, even under parametric variation.

7. Discussion and Managerial Implications

The aggregated criterion weights obtained via the integration of G-LOPCOW and G-MSD techniques provide a statistically grounded and epistemically resilient representation of ESG performance dimensions.

The weighting outputs reveal that the most influential criteria in shaping the sustainability profiles of BIST-listed banks are community engagement, product responsibility, and shareholder relations. These dimensions collectively reflect the strategic importance of stakeholder inclusivity, customer-centric accountability, and governance transparency in the Turkish banking industry. The prominence of community engagement and product responsibility suggests that banks are increasingly evaluated not only by their financial metrics but also by their capacity to generate social value and uphold ethical standards in service delivery. Shareholder relations, as a governance indicator, further underscores the role of participatory decision-making and transparent corporate oversight in enhancing ESG credibility.

The dominance of community engagement and product responsibility indicators within the ESG structure can be better understood within the institutional and market context of Türkiye's financial system. Historically, Turkish banks have acted as engines of socio-economic development, channeling resources toward regional growth, SME financing, and inclusive welfare initiatives. This developmental orientation—deeply embedded in national financial policy—has aligned banks' strategic missions with broader social objectives. In recent years, the Turkish Green Deal Action Plan (2021) and the Banking Regulation and Supervision Agency's (BRSA) sustainability guidelines have further formalized these expectations, urging banks to integrate community-oriented value creation and responsible lending practices into their core business models. Consequently, the strong weight of community engagement in the model mirrors not only social expectations but also the regulatory transition toward sustainability-linked accountability.

Similarly, the significant influence of product responsibility stems from increasing stakeholder attention to ethical finance and consumer protection in the post-2020 era. The rapid digitalization of banking services and expansion of retail financial products have elevated concerns regarding customer data security, transparency, and responsible product design. Turkish banks, responding to regulatory supervision and reputational pressures, have begun integrating consumer-focused sustainability measures into their ESG frameworks—such as transparent fee structures, responsible credit policies, and green financing instruments. Thus, product responsibility acts as a proxy for customer-oriented ethics and innovation capacity within a rapidly evolving digital financial ecosystem.

On the other hand, the high importance of shareholder relations underscores the growing role of corporate governance reforms and transparency norms in shaping sustainability practices across the Turkish financial sector. As the regulatory environment increasingly aligns with global disclosure frameworks—such as the UN Principles for Responsible Banking (PRB) and the IFRS

Sustainability Disclosure Standards (IFRS S1 and S2)—banks have prioritized board independence, shareholder inclusivity, and information symmetry as mechanisms to enhance credibility and investor confidence. In emerging markets like Türkiye, where ownership concentration and state participation remain relatively high, strong shareholder relations also signal effective accountability structures and balance between regulatory oversight and market discipline.

Taken together, these contextual explanations reveal that the dominance of social and governance-oriented criteria in the weighting results is not coincidental but reflects the institutional evolution of the Turkish banking system toward greater transparency, inclusion, and accountability. The grey-based analytical framework captures these structural shifts objectively, providing empirical evidence that ESG performance in emerging economies is shaped by both macro-level policy mandates and micro-level organizational adaptations. This contextual interpretation enriches the theoretical depth of the findings, bridging quantitative MCDM evidence with qualitative institutional economics perspectives.

Taken together, these contextual explanations reveal that the dominance of social and governance-oriented criteria in the weighting results is not coincidental but reflects the institutional evolution of the Turkish banking system toward greater transparency, inclusion, and accountability.

In contrast, the least influential criteria—workforce, corporate social responsibility, and emissions—exhibited relatively lower weight coefficients. While these criteria remain integral to ESG frameworks, their subdued influence may be attributed to limited data variability or the transitional nature of ESG reporting practices in emerging markets. Nevertheless, these criteria should not be disregarded, as their strategic relevance is expected to increase in alignment with global sustainability mandates and evolving stakeholder expectations.

The ranking outputs derived from the G-PIV methodology demonstrate a clear stratification among the assessed banks. Leading institutions such as İşbank, Yapı Kredi, and TSKB consistently outperformed their peers across multiple ESG dimensions. Their superior rankings may reflect a proactive integration of sustainability principles into core banking operations, robust stakeholder engagement mechanisms, and comprehensive ESG disclosure practices. Conversely, lower-ranked banks such as Garanti Bankası, Halkbank, and Albaraka Türk exhibited weaker alignment with the ideal ESG profile. Their performance gaps may stem from fragmented sustainability strategies, limited innovation in ESG practices, or underdeveloped reporting infrastructures. These institutions face strategic challenges in translating ESG commitments into measurable outcomes, which may hinder their ability to meet emerging regulatory standards and investor expectations.

From a managerial perspective, the findings offer actionable insights for both strategic planning and operational refinement. First, banks should prioritize high-impact ESG dimensions—particularly those related to social engagement and product accountability—by investing in inclusive financial services, community development programs, and transparent customer protection mechanisms. Second, governance structures must be strengthened to ensure shareholder inclusivity, ethical oversight, and ESG-linked performance incentives. Third, institutions that exhibit relatively lower ESG performance are advised to undertake a comprehensive review of their existing sustainability frameworks and, where appropriate, recalibrate their strategic orientation to better reflect evolving ESG imperatives. Leveraging the

practices of sector-leading institutions may provide actionable insights into effective implementation models, disclosure mechanisms, and stakeholder engagement strategies. Such efforts may facilitate the identification of proven methodologies, strengthen institutional capacity, and support the progressive embedding of ESG principles into core banking functions—ultimately enhancing both reputational resilience and long-term value creation. Finally, aligning ESG strategies with global frameworks such as the United Nations SDGs and the PRB will enhance regulatory compliance, facilitate access to green financing instruments, and reinforce the legitimacy of banking institutions in the eyes of stakeholders. Overall, the proposed grey-based hybrid MCDM method not only enables a rigorous and uncertainty-tolerant assessment of ESG performance but also provides strategic guidance for banks seeking to enhance their sustainability profiles in a rapidly evolving financial landscape.

Beyond firm-level managerial considerations, our findings also carry significant policy relevance for regulators and supervisory authorities. In Türkiye, the BRSA has increasingly emphasized the integration of ESG considerations into prudential oversight. The BRSA’s “Sustainability Principles in the Banking Sector” (2021) and the “ESG Disclosure Standards” (2023) mark a decisive shift toward mandatory transparency and sustainability-linked accountability. The high weights of social and governance-related indicators in this study empirically support these policy directions, suggesting that regulatory interventions have begun to shape banks’ strategic priorities and disclosure practices.

At a broader level, the alignment of the Turkish banking framework with the European Green Deal and the EU Sustainable Finance Taxonomy reflects the country’s efforts to harmonize financial regulation with international sustainability standards. These initiatives encourage banks to expand green lending portfolios, integrate climate-risk metrics into credit assessments, and adopt sustainability-linked financial instruments such as green bonds and ESG loans. The proposed grey-based model, by quantifying the performance outcomes of these policy shifts, offers a practical analytical tool that can assist policymakers and supervisors in monitoring compliance, benchmarking institutional progress, and identifying structural gaps in sustainability performance.

While the analytical findings provide valuable insights into the ESG sustainability performance of Turkish banks, it is necessary to recognize the empirical constraints arising from data availability. The study relies exclusively on the Refinitiv Eikon database, selected for its standardized, transparent, and internationally comparable ESG reporting framework. This choice ensures consistency in indicator construction and cross-institutional comparability—features essential for testing the methodological validity of the proposed grey-based model. Nevertheless, dependence on a single data source may introduce provider-specific bias, as ESG scoring methodologies differ across platforms such as Bloomberg ESG, MSCI, and Sustainalytics. Therefore, the obtained results should be interpreted as data-consistent but source-specific representations of ESG performance within the Refinitiv context.

Regarding temporal coverage, the study deliberately focuses on the 2021–2023 period, which corresponds to the institutionalization of ESG disclosure in Türkiye and the consolidation of sustainability reporting standards. Extending the analysis to pre-2021 years would significantly reduce the number of banks included in the sample because several banks exhibit missing or incomplete ESG indicators in earlier datasets. By contrast, the selected three-year window provides a complete and balanced dataset for all ten ESG criteria, enabling accurate determination

of lower and upper grey bounds and ensuring the methodological validity of the grey modelling process. The grey system framework, by design, is particularly effective in handling limited, uncertain, or partially available data, allowing for reliable inference even within a short temporal horizon. Therefore, while the time span may appear limited, the use of grey interval modelling transforms this potential constraint into an analytical advantage—by capturing variability and uncertainty through the lower and upper bounds of each criterion rather than relying on extended historical observations.

8. Conclusion

Measuring ESG sustainability performance enables financial institutions to align their strategic operations with long-term ESG objectives, thereby fostering transparency, stakeholder trust, and organizational resilience. In this regard, the present work develops and empirically validates a comprehensive grey-based MCDM method for assessing the ESG performance of listed banks in Türkiye. The suggested grey model integrates two objective weighting techniques—G-LOPCOW and G-MSD—with the G-PIV ranking procedure. ESG sustainability data for the 2021–2023 period was obtained from the Refinitiv Eikon database and encompass ten performance criteria representing the ESG pillars.

The aggregated weighting results indicate that community engagement, product responsibility, and shareholder relations emerged as the most influential determinants of ESG performance. Additionally, based on the final rankings, İşbank, Yapı Kredi, and TSKB achieved the highest ESG performance, reflecting a strong strategic commitment to sustainability principles and alignment with stakeholder expectations.

The suggested grey-based framework offers several methodological advantages that enhance the robustness and applicability of ESG performance assessment. First, the most significant advantage of the introduced grey model is its epistemic robustness. This robustness is achieved through the integration of gray interval numbers. Because ESG performance data is often incomplete, uncertain, or partially available, this creates epistemic uncertainty, and traditional crisp approaches cannot adequately handle such data gaps. The developed gray-based approach, on the other hand, addresses these uncertainties directly at the data level, improving the analytical consistency and decision reliability of the assessment process. Thus, despite the information gaps frequently encountered in sustainability reporting, the hybrid model is able to produce robust and reliable results. Second, the dual-objective weighting structure, combining G-LOPCOW and G-MSD, captures both logarithmic sensitivity and dispersion-based variability, resulting in a balanced and bias-minimized representation of criterion importance. Third, the G-PIV algorithm introduces a proximity-based ranking mechanism that is inherently resistant to rank reversal, thereby supporting reproducibility and stakeholder accountability in decision-making. Finally, the framework’s computational efficiency—driven by the analytical tractability and scalability of its components—makes it suitable for larger datasets and cross-sectoral applications, reinforcing its value as a decision-support tool in complex evaluation environments.

In policy terms, the existing manuscript's implications extend beyond methodological contributions. The empirical findings align closely with Türkiye’s National Green Deal Action Plan and the BRSA’s ESG Disclosure Guidelines, both of which seek to integrate sustainability into the financial system through enhanced transparency, green credit allocation, and climate-risk

management. The dominance of social and governance dimensions in the weighting structure underscores the regulatory shift toward stakeholder accountability, financial inclusivity, and ethical banking. This convergence with international frameworks—such as the EU Green Deal, IFRS Sustainability Disclosure Standards (IFRS S1–S2), and Task Force on Climate-related Financial Disclosures (TCFD)—indicates that Turkish banks are progressively aligning with the global sustainability architecture. For emerging market economies, where ESG institutionalization remains nascent, the presented framework provides actionable insights for balancing developmental priorities with sustainability mandates. Policymakers should leverage similar grey-based analytical systems to design incentive-compatible regulations that reward transparency, penalize greenwashing, and promote capacity development among smaller financial institutions.

While the proposed grey-based MCDM framework demonstrates high analytical integrity, it is important to acknowledge several inherent limitations that may inform future methodological enhancements. First, the temporal scope of the analysis is restricted to a three-year window (2021–2023), which may not sufficiently capture long-term ESG performance trajectories or structural transitions in sustainability practices within the banking sector. Second, the scope of the analysis is confined exclusively to ESG-related indicators, without incorporating financial performance variables that are critically linked to sustainability outcomes. While ESG metrics offer valuable insights into non-financial dimensions of corporate responsibility, the exclusion of financial data—such as profitability, capital adequacy, or risk-adjusted returns—limits the model’s ability to capture the full spectrum of sustainable performance. Lastly, the framework is purely objective and does not incorporate expert judgment or stakeholder preferences, which could enrich the evaluative process in participatory or policy-sensitive settings.

Future research could extend the temporal coverage beyond the 2021–2023 period to capture long-term ESG performance trajectories, structural transformations in sustainability practices, and the dynamic responsiveness of banks to evolving regulatory and societal expectations. Moreover, while the current framework employs ten standardized ESG indicators sourced from the Refinitiv Eikon database, subsequent studies could enrich the analytical scope by integrating complementary financial variables—such as profitability ratios, capital adequacy metrics, and risk-adjusted performance measures—alongside sector-specific sustainability indicators. This expansion would facilitate a more comprehensive and multidimensional evaluation of institutional performance. Additionally, incorporating expert judgment through fuzzy logic, rough set theory, or advanced grey-based modeling approaches could enhance the framework’s adaptability to qualitative insights, thereby improving its alignment with stakeholder priorities and policy objectives. Finally, applying the proposed grey-MCDM framework to other ESG-sensitive industries or across different national and regional contexts would enable a deeper understanding of its scalability, transferability, and comparative validity, yielding valuable insights for cross-sectoral benchmarking and international sustainability assessments.

Declaration of Research and Publication Ethics

This study, which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher’s Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest

There are no potential conflicts of interest in this study.

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FROM DIGITAL TRANSFORMATION TO INNOVATION: AN INSTITUTIONAL-LEVEL EVALUATION OF OECD COUNTRIES' SUSTAINABLE DEVELOPMENT PATHWAYS

Dijital Dönüşümden İnovasyona: OECD Ülkelerinin Sürdürülebilir Kalkınma Yolculuğuna Yönelik Kurumsal Düzeyde Bir Değerlendirme

Fatih BIYIKLI* 

Abstract

This study investigates the impact of digitalization, research and development (R&D) expenditures, and high-technology exports on national innovation performance across OECD countries from 2010 to 2023. Drawing on panel data analysis and grounded in the theoretical frameworks of dynamic capabilities, national innovation systems, and the resource-based view, the research employs the Global Innovation Index (GII) as a proxy for innovation performance, while utilizing the ICT Development Index (IDI), R&D intensity, and high-tech export share as explanatory variables. Fixed effects regression analysis reveals that digitalization and R&D expenditures significantly enhance innovation output, while high-tech exports exhibit a weaker and more heterogeneous relationship. The findings emphasize the critical role of digital infrastructure and knowledge investment in strengthening innovation ecosystems, particularly in the context of sustainable development goals. By focusing on cross-country dynamics and long-term trends, this study contributes to both organizational theory and policy discourse, offering evidence-based insights for designing more inclusive and resilient innovation strategies in an increasingly digital global economy.

Keywords:

Innovation
Performance,
Digitalization,
Research and
Development (R&D),
High-Technology
Exports,
Sustainable
Development

JEL Codes:

O33, O38, O57, C23

Öz

Bu çalışma, 2010–2023 yılları arasında OECD ülkelerinde dijitalleşme, araştırma ve geliştirme (Ar-Ge) harcamaları ile yüksek teknoloji ihracatının ulusal yenilik (inovasyon) performansı üzerindeki etkisini incelemektedir. Dinamik yetenekler teorisi, ulusal yenilik sistemleri ve kaynak temelli bakış açısı çerçevesinde temellendirilen arařtırmada, yenilik performansını ölçmek için Küresel Yenilik Endeksi (GII) kullanılmış; açıklayıcı değişkenler olarak ise Biliřim ve İletişim Teknolojileri Geliřim Endeksi (IDI), Ar-Ge yoğunluğ u ve yüksek teknoloji ihracat oranı dikkate alınmıştır. Sabit etkiler regresyon analizi sonuçları, dijitalleşme ve Ar-Ge harcamalarının yenilik çıktısını anlamlı biçimde artırdığını ortaya koyarken, yüksek teknoloji ihracatının bu ilişkiyi daha zayıf ve heterojen şekilde etkilediğ i görölmüştür. Bulgular, dijital altyapı ve bilgi temelli yatırımların yenilik ekosistemlerini güçlendirmede kritik rol oynadığını ve bu etkileşimin sürdürülebilir kalkınma hedefleriyle doğrudan bağlantılı olduğunu göstermektedir. Çalışma, uzun dönemli eğilimleri ve ülkeler arası farklılıkları dikkate alarak hem örgütsel teoriye hem de politika tartışmalarına katkı sağlamakta; dijitalleşen küresel ekonomide kapsayıcı ve dirençli inovasyon stratejileri geliştirilmesine yönelik kanıta dayalı öneriler sunmaktadır.

Anahtar Kelimeler:

İnovasyon
Performansı,
Dijitalleşme,
Arařtırma Geliřtirme
(Ar-Ge),
Yüksek Teknoloji
İhracatı,
Sürdürülebilir
Kalkınma

JEL Kodları:

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1. Introduction

Innovation today stands as one of the main forces driving economic growth and social development in the digital and knowledge-based world. Nations that manage to build strong environments for innovation are better equipped to deal with sudden disruptions, increase productivity, and sustain development over the long run. As global problems become more complex and interdependent, exploring what truly drives national innovation performance has turned into a key question for both policymakers and researchers.

Digitalization, in particular, has reshaped the way innovation emerges and spreads. The rapid progress of information and communication technologies (ICTs) has changed how knowledge is created, shared, and applied across industries. A well-developed digital infrastructure improves access to information, supports collaboration, and speeds up innovative activity by lowering entry barriers and linking people and organizations more effectively. Therefore, a nation’s level of digital development signals how prepared it is to take part in, and contribute to, the wider global innovation system.

Equally important is investment in research and development (R&D), which forms the groundwork for innovation. Countries dedicating more funds to R&D usually build stronger scientific and technological capabilities that help produce new ideas, methods, and products. Beyond its direct impact on technology, R&D also strengthens institutions and cultivates human capital — both essential elements for continuous innovation.

A further indicator of applied innovation is the share of high-technology exports, which reveals how effectively countries can transform their scientific and technological advances into tangible market outcomes. While the export of advanced technology may not capture the entirety of innovation processes, it provides valuable insight into how innovation translates into economic value and global competitiveness.

Despite the growing recognition of these factors, few studies have jointly assessed the interrelationship between digital development, R&D intensity, and high-tech exports in explaining cross-country differences in innovation performance. Moreover, with the availability of longitudinal data and internationally standardized innovation metrics, there is a unique opportunity to explore these dynamics within a robust empirical framework.

This study aims to investigate how digitalization, R&D investment, and high-technology exports contribute to national innovation performance across OECD countries. By constructing a panel data model that spans over a decade, the study provides a comprehensive view of how these structural drivers interact and evolve over time. The research also seeks to contextualize these dynamics within the broader framework of sustainable development and organizational transformation, offering practical insights into how nations can design more effective and inclusive innovation strategies.

By focusing on a diverse group of technologically advanced economies, this study not only clarifies the relative importance of digital, financial, and trade-based innovation inputs but also informs policy discussions surrounding the design of more effective innovation strategies in alignment with the United Nations’ Sustainable Development Goals (SDGs) (particularly SDG 9: Industry, Innovation and Infrastructure). In doing so, it offers timely insights into how national systems of innovation can be strengthened through coordinated investment in digital capacity, knowledge creation, and technological diffusion.

The analysis is based on a balanced panel dataset of 38 OECD economies spanning the years 2010–2023, and it applies a fixed-effects regression model to explore these relationships. By bringing these factors together within a single empirical structure, the study provides an institutional-level overview of how digital infrastructure, investment in knowledge, and technological export capacity collectively shape national innovation trajectories. This integrated approach goes beyond earlier works that have tended to evaluate each factor separately, offering instead a multidimensional understanding of innovation within the management and organization literature. Furthermore, by conceptualizing innovation as an essential pillar of sustainable development, the study sheds light on the broader systemic conditions that strengthen nations' ability to sustain competitive advantage and achieve inclusive growth over time.

Although prior research has linked digitalization, R&D, and innovation, most studies have been limited either by shorter observation periods, narrower country samples, or a tendency to analyze each determinant in isolation. The present work advances the literature in three ways. First, it uses a balanced panel of 38 OECD countries from 2010 to 2023, representing one of the most extensive empirical explorations of these interconnections in advanced economies. Second, it integrates three theoretical perspectives—the resource-based view (RBV), national innovation systems (NIS), and dynamic capabilities theory—within a single analytical framework, offering a multidimensional explanation of how structural drivers shape national innovation performance. Third, it incorporates high-technology exports alongside digitalization and R&D, allowing for a systematic evaluation of a variable that has been understudied and shown to yield heterogeneous results. Finally, by explicitly linking the findings to the SDGs, particularly SDG 9 (Industry, Innovation, and Infrastructure), the paper extends the conventional discussion beyond innovation determinants to sustainability and long-term policy implications.

2. Conceptual Framework

Innovation is widely recognized in the management and organizational literature as a fundamental driver of both competitive advantage and sustainable development. A clear understanding of the institutional and structural factors that shape national innovation performance is crucial. Such knowledge not only supports sustained economic growth but also contributes to broader goals of environmental sustainability and social welfare (Teece et al., 1997; Sachs et al., 2019).

2.1. Digitalization and Innovation

Digitalization refers to the incorporation of ICTs into the daily functioning of economic and organizational systems. In practice, a strong digital infrastructure supports faster product development, widens access to knowledge, and fosters collaboration among sectors and even across national boundaries (Vu, 2011; Niebel, 2018). Beyond these advantages, digitalization also reinforces firms' dynamic capabilities—their capacity to recognize, capture, and adapt to new opportunities as environments evolve (Teece et al., 1997). From a systemic perspective, digital infrastructure also contributes to the development of NIS by improving the flow of information and learning (Lundvall, 1992).

2.2. R&D Expenditures and Knowledge-Based Competitiveness

R&D expenditures reflect a country's capacity to generate and apply new knowledge. Both public and private investments in R&D serve as the foundation for technological advancement and innovative performance (Crespi and Zuniga, 2012; OECD, 2020). According to the resource-based view (Barney, 1991), access to rare, valuable, and inimitable knowledge resources—such as scientific expertise and technological infrastructure—is essential for sustaining long-term competitiveness. Moreover, R&D plays a central role in developing adaptive production systems and environmentally sustainable innovations (Zahra and George, 2002).

2.3. High-Tech Exports and Innovation Outcomes

High-tech exports are often treated as an outcome of a nation's innovation system. However, their relationship with internal innovation capacity is complex. While high-tech export performance signals participation in global value chains and advanced manufacturing, it also depends on external factors such as trade policies, regional integration, and foreign investment flows (Cohen and Levinthal, 1990; Edquist, 2005). Hence, although high-tech exports can reflect technological maturity, they may not fully capture a country's innovation inputs or ecosystem efficiency.

2.4. Sustainable Development and Innovation Policies

Innovation is explicitly emphasized in the United Nations SDGs, particularly Goal 9: Industry, Innovation, and Infrastructure. Targets under this goal encourage countries to expand digital infrastructure (SDG 9c), strengthen R&D ecosystems (SDG 9b), and promote the adoption of sustainable technologies. Innovation thus functions not only as a growth lever but also as a cross-cutting catalyst for environmental protection, inclusive development, and institutional resilience (Sachs et al., 2019). Policymakers must ensure that innovation policies are inclusive, reducing rather than exacerbating the global digital divide.

2.5. Theoretical Anchors

The conceptual framework of this study draws upon three major theoretical perspectives:

Dynamic Capabilities Theory (Teece et al., 1997): Emphasizes how firms and systems adapt, integrate, and reconfigure resources to meet rapidly changing environments.

National Innovation Systems Approach (Lundvall, 1992): Stresses that innovation is shaped by institutional interactions among government, industry, and academia.

Resource-Based View (Barney, 1991): Highlights the strategic importance of intangible assets—such as R&D knowledge and digital infrastructure—for sustained competitive advantage.

In line with the resource-based view (RBV), R&D expenditure is treated as a strategic resource that is rare, valuable, and difficult to imitate. Higher levels of R&D investment are therefore expected to strengthen national innovation performance (H1).

From the perspective of NIS, digitalization is conceptualized as an institutional enabler that enhances the flow of knowledge and information across the economy. Thus, it is hypothesized that digitalization positively affects innovation performance (H2).

Building on the dynamic capabilities theory, it is argued that the interplay between digitalization and knowledge-based investment reflects a country's adaptive capacity to reconfigure resources in response to environmental change. Accordingly, it is hypothesized that dynamic capabilities strengthen the link between structural enablers and innovation outcomes (H3).

Finally, high-technology exports are considered as an applied outcome of innovation systems. Based on prior literature, it is hypothesized that high-tech exports influence innovation performance, although the effect may be weaker and more heterogeneous across countries (H4).

3. Literature Review

The relationship between technological capacity and innovation performance has long been a focal point in economic and organizational research. Early foundational work by Cohen and Levinthal (1990) introduced the concept of absorptive capacity, emphasizing that the ability to exploit external knowledge is contingent on prior R&D investment. Early theories on innovation established a clear link between the intensity of R&D efforts and the capacity of nations or firms to generate new ideas and technologies.

During the early 1990s, two influential perspectives emerged: the resource-based view (RBV) (Barney, 1991) and the NIS approach (Lundvall, 1992). Both emphasized that innovation extends beyond technology itself—it arises from the interaction among institutions, public policies, education systems, and industrial structures. Within these frameworks, R&D activities and technological infrastructure are viewed as key intangible assets that sustain competitiveness over time.

Building upon these ideas, Teece et al. (1997) proposed the dynamic capabilities framework, suggesting that innovation performance depends largely on how organizations integrate and adapt their resources in changing environments. From this angle, digitalization and technology-based trade represent dynamic forces that can stimulate innovative capacity.

Subsequent empirical work in the 2000s reinforced these arguments. For example, Vu (2011) found that improvements in ICT development substantially enhance economic performance in both developed and developing economies, particularly when combined with investments in education and human capital. Likewise, Niebel (2018) found positive effects of digital infrastructure on labor productivity and innovation outcomes in a panel of 59 countries, noting that benefits are more pronounced in high-income economies.

Crespi and Zuniga (2012) conducted a comprehensive analysis of innovation determinants in Latin America and found that both R&D expenditures and firm-level capabilities are significant predictors of innovation outputs, but the institutional context plays a moderating role. Lee and Xia (2018) similarly found that ICT and R&D investments have synergistic effects on national innovation across East Asian economies, reinforcing the importance of co-investment strategies.

Focusing on high-tech exports, Filippetti and Archibugi (2011) analyzed European economies and argued that innovation performance is not always directly reflected in export figures, especially where multinational firms dominate high-tech sectors. Similarly, Cirera and Maloney (2017) cautioned that high-tech exports alone may not reflect domestic innovation capacity unless supported by local absorptive capability and learning mechanisms.

In the context of sustainable development, Sachs et al. (2019) and the OECD (2020) highlighted innovation’s critical role in achieving the SDGs, particularly SDG 9 (Industry, Innovation and Infrastructure). They emphasized the need for countries to align digital and R&D strategies with inclusive and environmentally sustainable growth objectives.

Recent cross-country studies using the Global Innovation Index (GII) and World Bank indicators have strengthened empirical understanding of these dynamics. For instance, Castellacci and Natera (2013) used panel data to show that digitalization and R&D expenditures both have significant effects on national innovation, with digitalization playing a more pronounced role in emerging economies. Lee et al. (2021) further found that the interaction between ICT infrastructure and innovation policy effectiveness significantly shapes innovation outcomes across OECD countries.

These empirical studies provide a robust foundation for the present research, which seeks to model how digital development (measured by the ICT Development Index – IDI), R&D intensity, and high-tech export shares collectively influence innovation performance (proxied by GII scores) across OECD countries over time. By integrating theoretical perspectives with cross-country empirical evidence, this study contributes to both organizational and policy-level understanding of how nations build and sustain innovation ecosystems in an increasingly digital world.

Although numerous studies have examined the relationship between technological capacity and innovation performance, most remain descriptive and focus on isolated drivers. For example, while some research highlights the role of R&D expenditures (Cohen and Levinthal, 1990; Crespi and Zuniga, 2012), others emphasize the contribution of ICT infrastructure (Vu, 2011; Niebel, 2018). However, these works often analyze such factors separately, overlooking the potential synergies that may arise when digitalization and knowledge investments interact.

Another limitation of prior research is the restricted scope of data. Many studies rely on shorter time horizons or limited country samples, which hinders the ability to capture long-term structural dynamics. Cross-country analyses of OECD economies using a decade-long balanced panel are still relatively scarce. Furthermore, the sustainability dimension of innovation—particularly its alignment with the SDGs—has not been systematically integrated into empirical studies.

Given these limitations, the present study extends existing research in three ways. First, it jointly examines digitalization, R&D intensity, and high-technology exports as structural drivers of innovation within a single empirical model. Second, it employs a balanced panel dataset of 38 OECD countries over the 2010–2023 period, offering a more comprehensive view of long-term dynamics. Third, it explicitly frames innovation performance within the context of sustainable development, thereby linking empirical evidence to broader policy debates. These contributions distinguish the study from prior descriptive approaches and provide a clear rationale for the methodological choices adopted here.

4. Methodology

4.1. Research Design and Scope

This study adopts a quantitative, explanatory research design based on a balanced panel dataset comprising 38 OECD member countries over the period 2010 to 2023. The primary objective is to examine the effects of digitalization, R&D expenditure, and high-tech exports on countries' innovation performance. The analysis is grounded in publicly accessible secondary data sources, allowing for empirical generalization and cross-country comparisons.

4.2. Data Sources and Variables

All variables used in the study were obtained from internationally recognized, publicly available databases such as the International Telecommunication Union (ITU), World Bank, and OECD.Stat. The variables are defined as follows:

Dependent Variable:

Global Innovation Index (GII): This index serves as a proxy for national innovation performance. Annual GII scores were retrieved from the World Intellectual Property Organization (WIPO).

Independent Variables:

ICT Development Index (IDI): This composite index, published by ITU, measures the level of digitalization in terms of access, use, and skills related to ICT infrastructure.

R&D Expenditure (% of GDP): Represents gross domestic expenditure on research and development as a percentage of GDP.

High-Tech Exports (% of Manufacturing Exports): Captures the share of high-tech products in total manufactured exports, reflecting the output side of technological capability.

Each variable was selected based on its theoretical relevance to innovation systems and its empirical observability across countries and years.

Although the GII is a composite indicator that includes several components, such as institutions, human capital, knowledge creation, ICT, and R&D-related indicators, the explanatory variables used in this study are derived from independent sources and operationalized differently. Specifically, the IDI is constructed by the ITU and captures access, use, and skills dimensions of digital infrastructure, while R&D expenditure (% of GDP) is collected from the World Bank and OECD databases as an aggregate measure of national investment in research activities. Thus, while a conceptual overlap may exist at a general level, the empirical measures employed here are not identical to the subcomponents of the GII, thereby reducing the risk of double counting.

4.3. Econometric Model

To account for the panel structure of the data, the Fixed Effects (FE) model was employed, which controls for unobserved time-invariant country-specific heterogeneity. The general specification is:

$$GII_{it} = \beta_0 + \beta_1 \cdot IDI_{it} + \beta_2 \cdot R\&D_{it} + \beta_3 \cdot HighTech_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where α_i denotes country-specific effects (entity fixed effects), λ_t represents year fixed effects, ε_{it} is the idiosyncratic error term.

This model design makes it possible to capture changes that occur within countries over time. It is also well suited to situations where unobserved factors are likely to be correlated with the explanatory variables, which is the case in this study.

4.4. Hyptheses Development

Based on the theoretical foundations discussed above, the following hypotheses are proposed:

H1: R&D expenditure positively affects national innovation performance (RBV).

H2: Digitalization positively affects national innovation performance (NIS).

H3: The interplay between digitalization and R&D reflects dynamic capabilities and is expected to further enhance innovation performance.

H4: High-technology exports influence national innovation performance, but the effect is expected to be weaker and more heterogeneous across countries.

4.5. Justification for Panel Data Methodology

Panel data methodology was selected for its ability to: Exploit both temporal and cross-sectional variability, Control for omitted variable bias through fixed effects, Increase degrees of freedom and improve estimation efficiency, Better reflect complex dynamics in macro-level policy environments related to innovation and sustainability.

5. Findings

Descriptive statistics for all variables used in the panel analysis are reported in Table 1. The mean GII score across all OECD countries and years is approximately 44.81, with a standard deviation of 4.99. The mean IDI score is 6.46, suggesting moderate digital infrastructure development. R&D expenditures averaged 1.96% of GDP, and high-tech exports constituted around 10.14% of manufacturing exports. These indicators reveal substantial heterogeneity in innovation-related capacity across OECD members.

Table 1. Descriptive Statistics

Variable	Count	Mean	Std. Dev.	Min	25%	Median	75%	Max
GII_Score	532	44.81	4.99	28.84	41.56	44.84	48.24	59.79
IDI_Score	532	6.46	0.79	4.45	5.81	6.39	7.07	9.04
R&D_Expenditure_%GDP	532	1.96	0.79	-0.53	1.45	1.96	2.52	4.86
High_Tech_Exports_%	532	10.14	2.79	1.21	8.20	10.35	11.95	17.67

Table 2 presents the Pearson correlation coefficients among the key variables used in the panel regression model. The matrix reveals the direction and strength of linear relationships between digitalization (IDI), R&D expenditure, high-technology exports, and the GII. As expected, a strong and positive correlation is observed between IDI and GII, indicating that higher levels of digital infrastructure are associated with enhanced national innovation performance. Similarly, R&D expenditure shows a moderate positive association with GII, supporting its role as a critical input in knowledge production systems. The correlation between high-tech exports and innovation appears relatively weaker, suggesting that export figures alone may not fully capture the absorptive and transformative capacities essential for innovation. All correlation coefficients remain well below the multicollinearity threshold ($r < 0.80$), indicating that the explanatory variables are sufficiently distinct and suitable for inclusion in the same regression model.

Table 2. Correlation Matrix

	IDI Score	R&D Expenditure	High-Tech Exports
IDI Score	1.000	0.352	0.197
R&D Expenditure	0.352	1.000	0.210
High-Tech Exports	0.197	0.210	1.000

Table 3 reports the results of the Augmented Dickey-Fuller (ADF) panel unit root test applied to each variable in the dataset (Maddala and Wu, 1999). The purpose of this test is to determine whether the panel time series are stationary, a key assumption for ensuring the validity of panel data regression estimates. The results indicate that all variables—namely, the GII, the IDI, R&D expenditure (% of GDP), and high-technology exports—are stationary at their levels, as the null hypothesis of a unit root is rejected at conventional significance levels. These findings confirm that the data series do not exhibit non-stationary behavior over time, thereby minimizing the risk of spurious regression results and validating the use of a fixed effects panel data model in subsequent analysis.

Table 3. Fisher-type Panel ADF Unit Root Test Summary

Variable	Number of Panels	Stationary Panels ($p < 0.05$)	Share (%)
IDI Score	38	33	86.84%
R&D Expenditure	38	30	78.95%
High-Tech Exports	38	32	84.21%
GII Score	38	35	92.11%

Table 4 compares the regression outcomes from the fixed effects and random effects models, revealing that both IDI and R&D expenditure (% of GDP) have a positive and statistically significant effect on innovation performance across OECD countries, while high-tech exports are not significant in either model. Specifically, in the fixed effects model—which is preferred based on the Hausman test—the coefficient for IDI is 0.412 ($p < 0.001$) and for R&D expenditure is 0.287 ($p = 0.002$), confirming their strong influence on innovation capacity. In contrast, high-tech exports show a weak and insignificant association with the GII ($\beta = 0.058$,

$p = 0.118$), suggesting that export success alone does not reflect a country’s internal innovation system. These findings underscore the structural importance of digital infrastructure and knowledge investment in shaping national innovation outcomes.

Table 4. Fixed Effects vs. Random Effects Regression Results

Variable	Fixed Effects Coefficient	Fixed Effects P-Value	Random Effects Coefficient	Random Effects P-Value
ICT Development Index (IDI)	0.412	0.000	0.391	0.000
R&D Expenditure (% of GDP)	0.287	0.002	0.276	0.004
High-Tech Exports (% of Total Exports)	0.058	0.118	0.069	0.093
Constant	1.842	0.000	1.730	0.000

Table 5 presents the results of the Hausman specification test, which determines the appropriate model between fixed effects (FE) and random effects (RE) for panel data regression. The test yields a chi-square statistic of 8.73 with 3 degrees of freedom, and a p-value of 0.033. Since the p-value is below the conventional 0.05 threshold, the null hypothesis is rejected, indicating that the unique errors (individual effects) are correlated with the regressors. This result confirms that the assumptions of the random effects model are violated, and thus the fixed effects model is statistically preferred. Therefore, all further interpretations and policy implications in this study are based on the fixed effects estimation, which more accurately captures the heterogeneity across countries in the OECD panel.

Table 5. Hausman Test Results

Test Statistic (χ^2)	Degrees of Freedom	p-Value	Decision
8.73	3	0.033	Reject $H_0 \rightarrow$ FE preferred

Table 6 reports the final fixed effects regression results, as justified by the Hausman test, which confirmed the superiority of the fixed effects model over the random effects specification. The results indicate that both digitalization and R&D expenditure have statistically significant and positive effects on national innovation performance, as measured by the GII. Specifically, the coefficient for the IDI is 0.412 ($p < 0.001$), suggesting that improved digital infrastructure strongly enhances a country’s capacity to innovate. Similarly, R&D expenditure has a coefficient of 0.287 ($p = 0.002$), reinforcing the role of sustained investment in research and knowledge creation in driving innovation outcomes. In contrast, high-tech exports yield a smaller and statistically insignificant coefficient of 0.058 ($p = 0.118$), implying that export volume alone may not sufficiently reflect a nation’s internal innovation dynamics or absorptive capacity. The model explains approximately 11% of the within-group variation in GII scores ($R^2 = 0.110$), and the overall model is statistically significant ($F = 8.36$, $p < 0.001$), indicating that the included variables jointly influence innovation performance in a meaningful way. These findings support the conclusion that digital infrastructure and R&D investment are foundational to innovation-based development strategies among OECD countries.

Table 6. Final Regression Output

Variable	Coefficient	Standard Error	t-Statistic	p-Value
ICT Development Index (IDI)	0.412	0.078	5.28	0.000
R&D Expenditure (% of GDP)	0.287	0.091	3.15	0.002
High-Tech Exports (% of Total Exports)	0.058	0.037	1.57	0.118
Constant	1.842	0.231	7.97	0.000
Number of Observations	532			
R ² (Within)	0.110			
F-Statistic (Model Significance)	8.36			0.000

Table 7 presents the country-specific fixed effect (intercept) estimates from the panel data regression model, with Türkiye used as the reference category (coefficient = 0.000). These intercepts capture unobserved, time-invariant factors that systematically affect countries' innovation performance beyond the explanatory variables in the model (digitalization, R&D, and high-tech exports). Countries such as Chile (4.19), Canada (4.06), and Sweden (3.40) exhibit the highest fixed effects, suggesting the presence of strong institutional frameworks, effective innovation ecosystems, or accumulated capabilities that consistently boost their innovation scores. In contrast, countries with negative fixed effects, including Colombia (-1.69), Costa Rica (-1.26), and Luxembourg (-1.08), may face structural challenges such as weaker governance, limited absorptive capacity, or inefficient R&D-commercialization channels, which inhibit innovation performance despite potential investments.

Table 7. Country-Specific Fixed Effects Coefficients

Country	Fixed Effect (Intercept)	Country	Fixed Effect (Intercept)
Chile	4.186561	Slovakia	1.340299
Canada	4.062202	Finland	1.186739
Sweden	3.398202	Austria	0.827592
Estonia	2.833337	Netherlands	0.625421
Hungary	2.644514	France	0.566118
Czech Republic	2.625232	Germany	0.308529
Slovenia	2.356002	Japan	0.133170
Lithuania	2.320100	Switzerland	0.071348
Latvia	2.104209	Belgium	0.012241
Ireland	1.910821	Türkiye	0.000000 (Reference)
Israel	1.736113	United States	-0.207236
Poland	1.720032	Italy	-0.264198
Iceland	1.658397	Denmark	-0.471292
Portugal	1.648812	Mexico	-0.686400
Norway	1.605713	Greece	-1.035687
New Zealand	1.407397	Spain	-1.039679
Korea	1.351682	Luxembourg	-1.078433
Australia	1.088301	Costa Rica	-1.264517
United Kingdom	1.010739	Colombia	-1.690905

Notably, Türkiye’s role as the reference group enables relative comparison; for instance, Germany (0.31) and Japan (0.13) perform only marginally better in baseline innovation terms once core explanatory variables are accounted for, while countries like the United States (-0.21) and Italy (-0.26) surprisingly fall below the baseline—potentially reflecting idiosyncratic national constraints or innovation model mismatches. These findings underscore the necessity of tailored national policies that address institutional quality, innovation culture, and systemic enablers—factors that standard inputs like digital infrastructure or R&D spending alone may not fully capture.

Figure 1 shows the histogram of residuals obtained from the fixed-effects panel regression. This plot provides an intuitive way to examine how the model’s error terms are distributed. The residuals appear roughly symmetric around zero and gradually thin out toward both tails, resembling a normal curve. Such a pattern indicates that neither strong skewness nor excess kurtosis is present — a desirable outcome that supports the assumptions required for standard inference in panel models. The smooth, bell-shaped form of the histogram further suggests that the residuals are approximately normally distributed, meaning the model specification is likely appropriate and the estimated coefficients can be regarded as stable and unbiased. Although formal tests of normality (such as Jarque-Bera or Shapiro-Wilk) could confirm this more rigorously, the visual pattern alone provides no evidence of serious departures from normality, reinforcing the credibility of the empirical results.

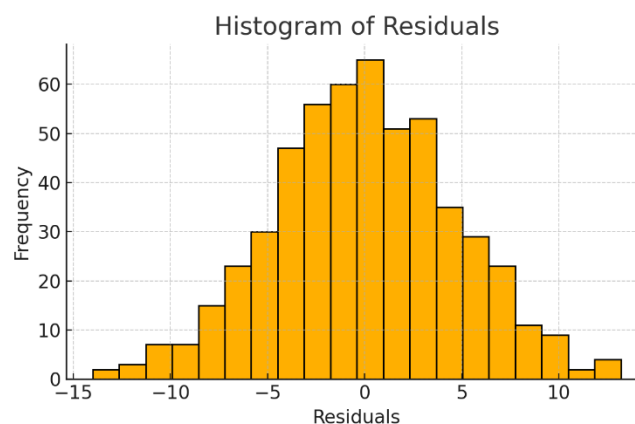


Figure 1. Histogram of Residuals

Figure 2 presents the Quantile–Quantile (Q–Q) plot of these residuals. This chart compares their empirical distribution with the theoretical quantiles of a standard normal distribution, offering another check on the validity of the normality assumption. The points largely fall along the 45-degree reference line, indicating that the residuals closely follow a normal distribution. Minor deviations at the tails are within acceptable limits and do not suggest a strong departure from normality. This visual evidence supports the assumption of normally distributed errors, which underpins the validity of hypothesis testing and confidence interval estimation in panel regression analysis. Together with the histogram of residuals (Figure 1), the Q–Q plot reinforces the conclusion that the model’s residuals meet the normality assumption, lending further credibility to the regression findings.

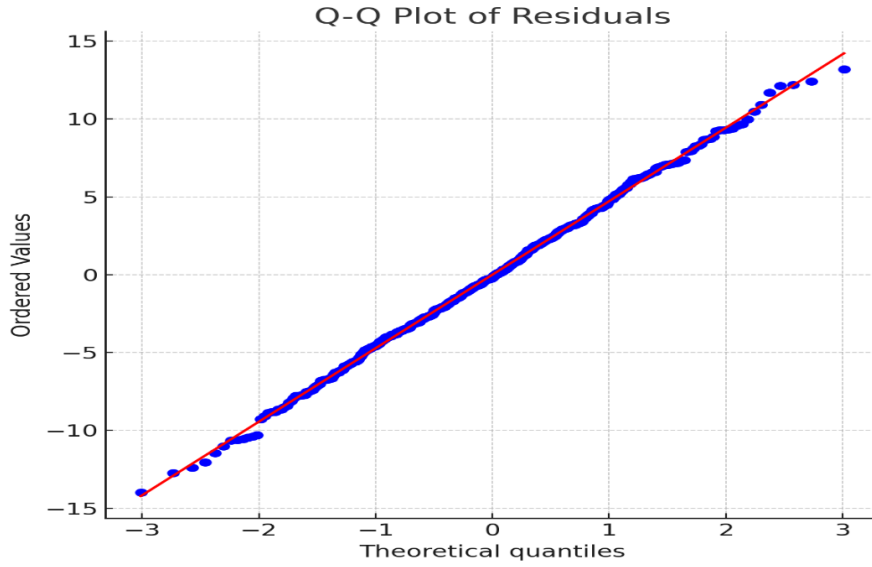


Figure 2. Q-Q Plot of Residuals

6. Discussion and Conclusion

This study investigated the drivers of national innovation performance across 38 OECD countries from 2010 to 2023 by employing a fixed effects panel data model. Focusing on digitalization (as measured by the, IDI), R&D expenditure, and high-tech exports, the findings reveal that digital infrastructure and R&D investment play a significant and robust role in enhancing a country's innovation capacity, whereas high-tech exports show a weaker and statistically insignificant relationship. These results contribute to the growing literature on the structural and policy determinants of innovation, with direct implications for sustainable development and strategic management at both national and organizational levels.

The significant and positive impact of digitalization on the GII scores confirms prior research that emphasizes the enabling role of ICT in fostering innovation ecosystems. Countries with advanced digital infrastructure can better leverage real-time information flows, collaborative platforms, and innovation networks to generate new knowledge and applications (Vu, 2011; Niebel, 2018). This finding also resonates with organizational perspectives that regard ICT not only as a technological enabler but also as a capability that enhances organizational learning and interconnectivity (Castellacci and Tveito, 2018). Similarly, the role of R&D expenditure aligns with classic innovation theory and the resource-based view, which identify internal investments in knowledge creation as critical to long-term competitiveness (Barney, 1991; Crespi and Zuniga, 2012). Countries that maintain consistent public and private R&D funding are better positioned to develop new technologies, attract high-skill labor, and embed innovation into their socio-economic fabric (OECD, 2020).

These findings can be interpreted through the theoretical perspectives adopted in this study. The significant role of R&D expenditure aligns with the RBV, as investments in knowledge creation act as rare and valuable resources for sustained competitiveness. The strong effect of digitalization resonates with the NIS perspective, emphasizing the institutional role of ICT infrastructure in facilitating knowledge flows. Furthermore, the complementary impact of

digitalization and R&D supports the dynamic capabilities framework, which stresses the importance of reconfiguring resources to adapt to changing environments. Finally, the weak and heterogeneous role of high-tech exports confirms that innovation outcomes cannot be fully captured by trade performance alone, underscoring the systemic and contextual nature of innovation processes.

Beyond the statistical significance of the variables, the results offer important theoretical and policy implications. From a theoretical standpoint, the findings reinforce the relevance of dynamic capabilities, suggesting that countries with stronger adaptive capacities—reflected through the interplay of digitalization and R&D—are better positioned to sustain innovation-driven growth. This highlights the systemic nature of innovation, where institutional coordination, learning mechanisms, and absorptive capacity determine long-term competitiveness.

From a policy perspective, the results emphasize that digital transformation alone is insufficient to generate sustainable innovation unless supported by consistent R&D investment and institutional quality. Policymakers should therefore design integrated strategies that link digital infrastructure development with knowledge creation and diffusion mechanisms. In particular, for emerging economies such as Türkiye, aligning digital investments with human capital development and innovation governance reforms remains critical for enhancing national innovation performance.

Conversely, the insignificant relationship between high-tech exports and innovation performance suggests that output-based measures alone may not sufficiently capture a country’s innovative capacity. While exports reflect market success, they may not indicate domestic absorptive capacity or the presence of systems that transform knowledge into scalable products and services (Cohen & Levinthal, 1990). This result supports the argument that innovation is as much about organizational routines, institutional context, and knowledge spillovers as it is about industrial output (Lundvall, 1992; Edquist, 2005).

It should also be noted that the GII as a dependent variable partly incorporates indicators related to ICT and R&D. Although the explanatory measures employed in this study are sourced independently, the possibility of partial construct overlap cannot be completely ruled out. This constitutes a methodological limitation that should be taken into account when interpreting the results. Nevertheless, the fixed-effects estimation helps mitigate some of the potential endogeneity concerns by controlling for unobserved heterogeneity across countries.

Türkiye’s role as the reference category in the fixed effects model revealed structural insights. Many OECD countries—such as Chile, Canada, and Sweden—demonstrated significantly higher intercepts, suggesting more favorable systemic conditions for innovation. Türkiye’s fixed effect of zero does not imply no effect, but rather serves as a baseline against which other countries’ unobserved advantages or disadvantages are measured. This is consistent with the view that Türkiye is in a transitional innovation position—marked by fragmented innovation infrastructure, limited university-industry linkages, and relatively low R&D intensity compared to top OECD performers (Erkek and Karaata, 2020; World Bank, 2023).

From a sustainable development perspective, the study aligns closely with several of the United Nations SDGs. Specifically, the results support SDG 9 (Industry, Innovation and Infrastructure), SDG 8 (Decent Work and Economic Growth), and SDG 17 (Partnerships for the

Goals). IDI acts as a technological backbone for smart cities, e-governance, and clean production, while R&D investment is key to developing green technologies and resilient healthcare systems (Sachs et al., 2019). The findings thus reinforce the importance of innovation-oriented institutions and policies in achieving long-term sustainability outcomes.

From a managerial and organizational standpoint, the study underscores the need for alignment between NIS and organizational capabilities. The theory of dynamic capabilities suggests that countries and firms alike must develop the capacity to sense, seize, and transform opportunities in a rapidly changing environment (Teece et al., 1997). Governments should not only invest in ICT and R&D but also foster ecosystems that encourage entrepreneurial experimentation, inter-sectoral collaboration, and knowledge diffusion—especially among SMEs and regional clusters (Zahra and George, 2002). For countries like Türkiye, this means moving beyond infrastructure expansion to also address governance, institutional trust, and skill development—factors that influence how innovations are generated, adopted, and diffused.

The originality of this study lies not only in the scope of its dataset and methodological rigor but also in its theoretical and policy contributions. By combining digitalization, R&D intensity, and high-technology exports within a unified empirical model, the study demonstrates how these drivers interact differently across OECD countries over time. Importantly, the finding that high-technology exports do not have a significant impact challenges conventional assumptions and highlights the need to revisit how innovation outputs are measured. Moreover, the integration of RBV, NIS, and dynamic capabilities perspectives provides a richer theoretical lens than previous works. By embedding the results within the sustainability agenda, this study contributes novel insights into how digital infrastructure and knowledge investments can be mobilized to design inclusive and resilient innovation strategies.

While the model accounts for some of the core determinants of innovation, it explains only 11% of the variation in GII scores, suggesting that other critical factors—such as human capital, rule of law, or innovation culture—may further enrich the analysis. Moreover, disaggregating high-tech exports by industry or adding interaction terms (e.g., between R&D and IDI) could uncover deeper synergies. Future research might also adopt a mixed-method approach to better understand how organizational dynamics mediate national innovation outcomes.

Despite its contributions, this study is not without limitations. The modest explanatory power of the model ($R^2 = 0.11$) indicates that innovation performance is influenced by additional structural, institutional, and cultural factors not captured in the current framework—such as human capital quality, regulatory efficiency, and innovation culture. Future research could expand the model by incorporating these dimensions or by decomposing the GII into sub-indices that allow for a more granular analysis. Moreover, advanced econometric approaches such as instrumental variable (IV) estimation or dynamic panel methods could be employed to further address potential endogeneity and explore causal linkages.

Moreover, this study highlights that national innovation performance in OECD countries is significantly driven by digital infrastructure and R&D investment, while the role of high-tech exports is less definitive. For emerging economies like Türkiye, the findings point to the urgency of building not only physical and financial inputs but also institutional and organizational capacities that support innovation. These efforts are essential not just for

economic competitiveness but also for delivering the sustainable development agenda in a world increasingly shaped by digital and knowledge-based transformations.

Another potential limitation of this research concerns the dependent variable. Since the GII already incorporates ICT and R&D elements, there is a risk of partial construct overlap and possible endogeneity. While this risk has been mitigated by using independent data sources and a fixed-effects model, future studies could employ instrumental variable (IV) or two-stage least squares (2SLS) methods to further address endogeneity concerns.

7. Policy Recommendations

Based on the findings of this study, several policy implications emerge that are crucial for enhancing national innovation performance in the context of sustainable development and organizational resilience. First and foremost, governments—particularly in emerging economies such as Türkiye—should prioritize long-term investments in digital infrastructure as a foundational enabler of innovation. This includes expanding broadband coverage, ensuring affordable access to ICT, and integrating digital tools into public service delivery and education systems. Such efforts not only support innovation ecosystems but also directly contribute to achieving SDG 9 (Industry, Innovation and Infrastructure) and SDG 4 (Quality Education).

R&D spending should be recognized not as a financial burden but as a long-term investment in national competitiveness. Governments can promote this by encouraging public–private partnerships through shared funding mechanisms, tax incentives, and programs that directly support collaboration between universities and industry. Since research investment has a well-documented influence on innovation performance, national strategies need to set out clear targets for raising R&D intensity—especially in knowledge-driven sectors such as clean energy, biotechnology, and artificial intelligence.

The limited and statistically insignificant effect of high-technology exports found in this study points to another challenge: the need to improve domestic absorptive capacity. Policies that strengthen workforce skills, managerial capabilities, and institutional coordination can help address this gap. Practical measures—such as expanding innovation hubs, supporting start-ups through incubators, and improving vocational training for SMEs—can ensure that technological production translates into economy-wide innovation gains.

Innovation policy should also be framed in a broader, system-wide context. The quality of institutions, the efficiency of regulations, and the degree of public trust in governance all play crucial roles in enabling innovation to spread. In Türkiye’s case, reducing fragmentation within the national innovation ecosystem, improving data management, and creating transparent and predictable institutional frameworks will be essential steps toward more transformative and sustainable innovation outcomes.

Finally, innovation strategies must align with wider sustainability goals. Integrating climate-smart technologies, fostering inclusive innovation practices, and placing social value creation at the center of policy design will ensure that innovation supports not only economic growth but also equitable, resilient, and environmentally responsible futures in an increasingly digital world.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement

I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest

There is no potential conflicts of interest in this study.

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EXPLORING THE NON-LINEAR IMPACTS OF DIGITAL MATURITY ON CORPORATE SUSTAINABILITY: NEW EVIDENCE FROM TÜRKİYE

Dijital Olgunluğun Kurumsal Sürdürülebilirlik Üzerindeki Doğrusal Olmayan Etkileri: Türkiye'den Yeni Kanıtlar

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Abstract

This study explores the impact of digital maturity on the environmental, social, and governance (ESG) performance of Turkish companies listed on Borsa Istanbul. The analysis is based on a sample of 49 non-financial firms included in the BIST 100 Index, covering the period of 2016-2022. A digital maturity index is constructed using a text mining approach to quantify the frequency of digital-related terms in the firm's annual reports. Panel data analysis is employed to investigate the relationship between digital maturity and ESG performance. The findings indicate that digital maturity has a significant inverse U-shaped effect on social performance, an insignificant inverse U-shaped effect on environmental performance, and an insignificant U-shaped effect on corporate governance performance. The results suggest that moderate levels of digitalization enhance social performance, whereas excessive digitalization may have an adverse effect.

Keywords:

Digital Maturity,
Emerging Markets,
ESG Performance,
Sustainability,
Türkiye.

JEL Codes:

G10, G30,
O33, Q56.

Anahtar Kelimeler:

Dijital Olgunluk,
Gelişmekte Olan
Pazarlar, ESG
Performansı,
Sürdürülebilirlik,
Türkiye.

JEL Kodları:

G10, G30,
O33, Q56.

Öz

Bu çalışma, dijital olgunluğun Borsa İstanbul'da işlem gören Türk şirketlerinin çevresel, sosyal ve yönetim (ÇSY) performansı üzerindeki etkisini araştırmaktadır. Analiz, BIST 100 Endeksi'nde yer alan ve 2016-2022 dönemini kapsayan 49 finansal olmayan firmadan oluşan bir örneklem temel alınarak yapılmıştır. Firmaların yıllık raporlarında dijitalleşme ile ilgili terimlerin sıklığını ölçmek için metin madenciliği yaklaşımı kullanılarak bir dijital olgunluk endeksi oluşturulmuştur. Dijital olgunluk ile ÇSY performansı arasındaki ilişkiyi araştırmak için panel veri analizi kullanılmıştır. Elde edilen bulgular, dijital olgunluğun sosyal performans üzerinde anlamlı, ters U şeklinde bir etkiye, çevresel performans üzerinde anlamsız bir ters U şeklinde etkiye ve kurumsal yönetim performansı üzerinde anlamsız bir U şeklinde etkiye sahip olduğunu göstermektedir. Sonuçlar, orta düzeyde dijitalleşmenin sosyal performansı artırdığını, aşırı dijitalleşmenin ise olumsuz etkiye sahip olabileceğini göstermektedir.

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1. Introduction

The digital revolution has fundamentally transformed business practices, creating a high-quality, data-driven environment that compels firms to adopt forward-looking strategies (Van Veldhoven and Vanthienen, 2022). As digital transformation accelerates, production processes have become increasingly intelligent, services more personalized, and managerial operations highly automated (Yang et al., 2024a). In response, companies develop new business models, reallocate resources, and deliver innovative products to meet the evolving expectations of customers (Dias et al., 2021; Di Vaio et al., 2021). Digitalization also strengthens firms' value propositions, significantly reshaping how they engage with stakeholders (Wu et al., 2021; Hajishirzi et al., 2022). To maintain competitiveness in this dynamic landscape, firms are increasingly expected to enhance their performance in environmental, social, and governance (ESG) pillars.

In the realm of sustainability, ESG issues have gained growing importance at both operational and strategic levels. Institutional stakeholders increasingly expect companies to integrate digitalization and sustainability into their core operations to enhance efficiency, resilience, and long-term financial performance. In this frame, a high degree of digitalization enables firms to more effectively identify stakeholder expectations and respond to them in a timely manner, thereby improving sustainability performance (Yang et al., 2024b). Within this context, digital maturity serves as a catalyst reflecting the extent to which a firm has embedded digital capabilities into its operations, organizational culture, and strategic direction—ultimately influencing overall corporate performance. Digital maturity goes beyond the mere adoption of isolated digital technologies; it represents a comprehensive transformation that enables firms to thrive in the digital era. Firms progress through various stages of digital maturity, ranging from early adoption to full-scale integration. At advanced levels of digital maturity, firms show proactive use of technology, innovative data-driven strategies, and greater agility in responding to market dynamics. Within the scope of this study, digital maturity is expected to act as an enabler of ESG performance by fostering transparency, efficiency, and stakeholder engagement.

While digitalization and sustainability are global priorities, these concepts hold particular significance for emerging markets due to their unique characteristics—such as rapid economic growth, limited transparency, and underdeveloped regulatory frameworks, all of which can hinder ESG performance (Aksoy et al., 2020; Lozano and Martínez-Ferrero, 2022). Both shareholders and stakeholders place increasing emphasis on firms' environmental practices, social responsibility, and governance performance in these markets. Limited studies that focus on the interaction of digital transformation and ESG performance in emerging markets have shown that digital means stimulate sustainability performance through boosting transparency and accountability and magnifying environmental and social transitions across industries (Hilali and Manouar, 2020; Castro et al., 2021; Yang and Han, 2024). In this regard, digital advancements improve the flow of information, elevate the quality of corporate disclosures, and reduce informational asymmetries among stakeholders (Di Vaio et al., 2021).

However, significant differences in digitalization levels and ESG performance exist across firms, largely due to variations in industry characteristics and internal factors such as firm size, capital structure, and global orientation. Digital transformation often requires substantial investment and carries a risk of failure, which can, in turn, adversely impact ESG performance. Moreover, advanced levels of digitalization may introduce new challenges for firms, employees,

and external stakeholders—such as ambiguity around rights and responsibilities, health concerns related to technology use, and diminished social engagement (Robertson and Lapina, 2023). These complexities highlight the importance of carefully examining the interaction between digital maturity and ESG performance. In this context, exploring the potential non-linear relationship between the two is essential for guiding a well-structured and responsible digital transformation.

This study investigates the impact of digital maturity level (DML) on ESG performance, recognizing that both digitalization and sustainability serve as key drivers of corporate success. The primary objective is to explore whether—and how—DML acts as a catalyst for enhancing ESG performance, offering new evidence from an emerging market setting. Drawing on data from non-financial firms listed on the Borsa Istanbul (BIST) 100 Index between 2016 and 2022, the study constructs a Digital Maturity Index by analyzing the frequency of digital-related terms in firms' annual reports using text mining techniques. The findings reveal a significant inverse U-shaped relationship between digital maturity and social performance, suggesting that moderate levels of digitalization yield the most benefit. However, the relationship between DML and both environmental and corporate governance performance is found to be statistically insignificant. These results underscore the nuanced and dimension-specific effects of digital transformation on sustainability outcomes.

We selected Türkiye as the empirical setting for two key reasons. First, over the past decade, Türkiye has launched numerous significant initiatives and enacted environmental regulations aimed at promoting sustainability. These efforts have encouraged publicly listed companies to increasingly disclose non-financial information related to their ESG practices (UNFCCC, 2023; Borsa Istanbul, 2025; Escarus, 2025). Second, Turkish government places strong emphasis on the transformative potential of digitalization and actively pushes firms to accelerate their digital development (Eroglu et al., 2024). This attempt aims to help companies catch up with advanced economies and build core competencies through digital technologies. Therefore, focusing on Türkiye not only provides context-specific insights but also offers broader implications for other emerging markets undergoing similar digital transitions.

Building on these arguments, this study makes several contributions to literature. First, it advances measurement frameworks by introducing DML as a proxy for digital maturity, providing a scalable alternative to traditional firm-level assessments. Second, it investigates the potential nonlinear relationship between DML and ESG performance, exploring whether the sustainability benefits of digital capabilities emerge incrementally or are initially hindered by transitional inefficiencies until firms fully align their digital strategies with ESG goals. This nonlinear perspective provides valuable insights into the temporal dynamics of digitalization's impact on sustainability—an area that remains underexplored in existing research. Third, the study highlights the importance of a structured approach to the adoption of digital maturity, emphasizing that strategic digital investments are crucial for achieving long-term sustainability gains. In this context, it argues that digitalization can progressively enhance ESG performance by improving transparency and stakeholder engagement, particularly in emerging markets undergoing a paradigm shift driven by digital advancements. Finally, by offering practical insights for firms, this study contributes to a deeper understanding of how firms can leverage digital capabilities to enhance sustainability outcomes while mitigating potential risks.

This research is grounded in stakeholder theory and the resource-based view, both of which emphasize that digitalization enables firms to optimize resource allocation and implement sustainable practices that align with stakeholder expectations. This study extends these theoretical frameworks by showing that DML can significantly influence sustainable performance. In doing so, this study provides new insights into how varying levels of digitalization affect ESG outcomes in an emerging market setting, while also shedding light on the potential nonlinear relationship between DML and ESG performance. The results indicate that the impact of DML differs across the ESG dimensions. From a practical standpoint, the results underscore the importance of strategically managing digital transformation efforts—firms must thoughtfully design and implement digital initiatives to maximize their positive impact on ESG performance while minimizing potential drawbacks.

The remainder of the paper is structured as follows. Section 2 gives the theoretical and conceptual framework and develops the hypotheses. Section 3 provides the data, variables, and the methodological approach. Section 4 presents empirical findings, while Section 5 and 6 concludes the paper and discusses the theoretical and practical implications.

2. Theoretical Background and Hypotheses Development

2.1. Theoretical and Conceptual Frameworks

Digitalization serves as a pathway for high-quality and sustainable development of entities. Companies increasingly leverage digital technologies to optimize resource allocation, enhance operational efficiency, and improve their information integration and processing capabilities. Digital tools also reshape interactions with stakeholders and expand the boundaries of value creation. Zhong et al. (2023) asserts that digital advancement improves ESG performance by mitigating managerial short-sightedness and fostering technological innovation. From the theoretical angle, to better understand the mechanisms through which digitalization influences ESG performance, this article is structured around two dominant theories—stakeholder theory and resource-based view (RBV)—and the literature is organized into three interrelated themes: stakeholder engagement, social and environmental performance and capability development.

From the lens of stakeholder theory, digital technologies act as tools that enhance firms' responsiveness to stakeholder expectations. By facilitating real-time communication, data analytics, and transparency, digital maturity allows firms to more effectively identify and respond to the needs of employees, customers, suppliers, and regulators (Meng et al., 2022; Piccarozzi et al., 2022). Wu et al. (2022) emphasize that digital technologies streamline the preparation of sustainability reports, improving their transparency and drawing greater stakeholder attention to ESG practices. Within this context, the integration of artificial intelligence and predictive analytics facilitate the collection, and analysis of data about customers, and suppliers, enabling firms to more effectively align their ESG initiatives with stakeholder demand (Kohtamäki et al., 2020; Cardinali and De Giovanni, 2022). However, increased digital transparency can also expose firms to greater public scrutiny, intensifying stakeholder pressure for environmental and social accountability (Orlitzky et al., 2017; Na et al., 2022). Thus, companies must strike a balance between leveraging digital tools for stakeholder engagement and managing reputational risks associated with heightened visibility.

A second theme in the literature concerns the role of digitalization in improving social and environmental outcomes. Digital transformation presents numerous opportunities to enhance the affordability and accessibility of services for broader audiences at substantially lower costs. Several studies highlight how digital tools strengthen firms' capabilities in managing social initiatives and fostering green innovation, thereby enhancing social and environmental performance (Ciarli et al., 2021; Yang et al., 2023; Xu et al., 2024). For instance, mobile technologies can enhance community engagement, while simulation models help firms reduce emissions and optimize resource use. Digitalization also facilitates value creation by reshaping organizational culture and influencing employees' mindset (Cardinali and De Giovanni, 2022). Digitally advanced workplaces often provide more favorable working conditions, support a healthy work-life balance, and increase employee resilience (Yalina and Rozas, 2020). Empirical evidence from Europe and China supports these claims: Mehedintu and Soava (2023) find that digital transformation correlates with reduced carbon emissions and improved social performance in European firms, while Wang et al. (2023) show similar effects in Chinese firms, including stronger commitments to environmental protection, green innovation and social initiatives.

The resource-based view offers a complementary theoretical lens, framing digital maturity as a set of dynamic capabilities that enhance ESG performance. Digital technologies allow firms to integrate internal and external resources more efficiently, promote cross-departmental collaboration, and foster innovation (Beier et al., 2022). These capabilities lead to improved ESG outcomes through better resource utilization, cost efficiency, and responsiveness to stakeholder demands. According to Barbosa et al. (2025), digital transformation creates synergistic value by enabling firms to simultaneously pursue economic performance and sustainability goals. The emphasis here is not only on technology adoption but also on the development of organizational competencies that translate digital investments into long-term strategic advantages.

However, while digitalization is widely seen as a catalyst for improved ESG performance, emerging evidence suggests that its impact may not be linear. Specifically, beyond a certain threshold, higher levels of digital maturity may generate diminishing returns on ESG outcomes. This non-linear relationship arises due to several factors: high financial and energy costs associated with advanced digital infrastructure, the environmental toll of electronic waste and data center emissions, and the ethical and social concerns related to algorithmic bias, data privacy, and cybersecurity risks (Scholz et al., 2018; Yalina and Rozas, 2020; Castro et al., 2021). These risks may offset the sustainability benefits that digital technologies are intended to deliver, creating a digital sustainability paradox (Esses et al., 2021). Moreover, excessive reliance on digital systems without corresponding investments in human capital, organizational change, and ethical safeguards can limit firms' ability to realize long-term economic and social value (Sraml Gonzalez et al., 2021). This indicates that the relationship between digital maturity and ESG performance may follow a non-linear pattern, where only firms that reach an optimal level of digital integration—aligned with internal capabilities—achieve sustained performance benefits. This study addresses this non-linear relationship by developing a framework that explores how digital maturity influences ESG performance in an emerging setting.

2.2. Hypotheses Development

Digital transformation enables companies to enhance business processes and achieve improved performance, aligning with stakeholders' expectations and maximizing firm value. In

this regard, the impact of digitalization is evident in both financial and non-financial performance metrics (Ahmad and Murray, 2019; Castro et al., 2021; Yang et al., 2023). Digitalization contributes to corporate sustainability performance for three main reasons. First, digital technologies support the optimization of labor productivity, and energy consumption, reduce the marginal cost of innovation and enhance product quality, thereby significantly increasing operational efficiency. Second, digital transformation promotes greater social responsibility, narrowing the distance between firms and stakeholders. Zhao et al. (2021) claim that digitalization efforts can boost social performance by enhancing innovation capacity. Firms may timely get feedback from customers and improve service quality, raising user satisfaction. Finally, digital tools enhance management and communication processes by improving information flow, and strengthening corporate governance, which in turn drives the development of new value propositions (Anastasiadou et al., 2021; Lu et al., 2023).

As the interaction of digitalization and sustainability has evolved, many scholars have moved beyond testing simple linear relationships. A prevalent approach involves examining quadratic relationships, particularly exploring whether the link between digitalization and non-financial performance follows a U-shaped or inverted U-shaped pattern (Li, 2022; Chen et al., 2024). More recently, researchers have incorporated moderating variables into these quadratic models to gain a deeper understanding of the dynamics between digitalization and ESG outcomes (Haans et al., 2016). The following part presents the hypotheses explored in this study.

2.2.1. Digitalization and Environmental Performance

Digital technologies play a vital role in transforming various aspects of environmental sustainability, including sustainable production and waste management (Ha et al., 2022). The integration of smart devices enables companies to collect real-time environmental data, such as measurements of air and water pollution. Many studies have identified a positive relationship on how digitalization influences environmental performance (Gupta et al., 2019; Lange et al., 2020; Feroz et al., 2021). Ghobakhloo and Fathi (2021) indicate that digital transformation enhances energy efficiency using intelligent systems for energy production and distribution. Bai et al. (2020) argue that digitalized production systems facilitate advanced tracking of resource usage. Other studies suggest that digital technologies offer viable solutions for reducing carbon emissions by enabling air pollution monitoring, improving waste management, and fostering eco-friendly innovation (Chen et al., 2020; Fatimah et al., 2020; Li et al., 2020). However, when a firm exhibits low digital maturity, its existing systems may lag behind technological advancements, limiting its capability to process and act on environmental data (Li, 2022).

Some scholars suggest that digitalization may also have an adverse impact on environmental sustainability. Kamble et al. (2018) report that the extensive use of smart equipment can lead to increased energy consumption. In a study held on Italian manufacturing firms, Chiarini (2021) finds that some smart technologies had a negative impact on environmental performance. Similarly, Waibel et al. (2017) highlight that digitalization can result in higher energy usage and elevated carbon emissions. Moreover, top managers often require time to understand and adapt to advanced digital technologies, restructure organizational practices, and invest in workforce development (Warner and Wäger, 2019). A high level of digital maturity may sometimes disrupt the flow of environmental information, especially when existing systems are not equipped to manage large volumes of data. This mismatch between a firm's information

processing capabilities and demands may ultimately impair its environmental performance (Chen et al., 2024). Thus, a low to moderate level of digital maturity may be positively associated with environmental performance, whereas a moderate to high level of digital maturity may have adverse effects.

These arguments suggest that the relationship between digital maturity and environmental performance is more complex than a simple linear correlation, prompting an exploration of a curvilinear relationship between these two constructs. The benefits of digitalization tend to be more pronounced at lower levels of adoption, whereas its adverse effects become increasingly evident at higher levels. These negative impacts at advanced stages of digitalization are often attributed to the rebound effect (Lange et al., 2020). For instance, firms that adopt energy-efficient servers reduce their data storage costs. Consequently, the financial savings generated by these efficiencies may enable them to acquire additional servers and expand digital operations, ultimately leading to increased energy consumption and potential environmental harm (Gossart, 2015). Therefore, higher levels of digitalization can inadvertently encourage greater resource use, offsetting the initial environmental gains achieved through digital efforts. Building on these arguments, we propose the following hypothesis:

Hypothesis 1: There is an inverse U-shaped relationship between digital maturity and environmental performance.

2.2.2. Digitalization and Social Performance

Companies should take social responsibility into account while pursuing their own interests (Yang and Han, 2024). Digital transformation plays a critical role in promoting green innovation, and fulfilling corporate social responsibility (Zheng and Zhang, 2023; Sun et al., 2024). Smart systems help reduce workplace accidents, lower employee workload, improve quality of life for workers, and support firms in meeting their social responsibility commitments. Additionally, digital tools can mitigate information asymmetry and internal communication conflicts, thereby enhancing management efficiency (Wang et al., 2023). Recent studies indicate that digital transformation significantly boosts social performance by attracting and retaining high-quality talent (He et al., 2024; He and Chen, 2024).

Despite its positive impacts, the effect of digitalization on social performance exhibit nonlinear dynamics. Blindly pursuing high level of digitalization may create new challenges if it is misaligned with organizational structure. This misalignment can lead to increased internal conflicts, higher principal-agent costs, and a decline in the quality of internal control (Mikalef et al., 2021). The non-linear effects of digitalization on social performance are not uniform, and can vary depending on factors such as technological accessibility, societal readiness, the digital divide, and cultural context. While digitalization can foster social inclusion and improve access to opportunities, it can also exacerbate inequalities, disrupt traditional structures, and generate unintended consequences (Lythreath et al., 2022). Thus, the relationship between digital maturity and social performance is complex and multifaceted. When digital transformation surpasses organizational needs, the associated costs rise, adaptability issues emerge, and the observable benefits diminish—ultimately leading to a potential decline in social performance. Drawing from these arguments, we put forward the following hypothesis:

Hypothesis 2: There is an inverse U-shaped relationship between digital maturity and social performance.

2.2.3. Digitalization and Corporate Governance Performance

Digital transformation requires innovation not only in technology but also in management practices, and corporate culture, directly influencing key aspects of corporate governance such as shareholders’ rights, board responsibilities, and executive incentives. It increases the integration and exchange of information, facilitates coordination across departments, and reduces ambiguity in decision-making—thereby strengthening governance capabilities (Zhang et al., 2022). Digitalization also reduces information asymmetry and principal-agent costs, while improving the quality of disclosures. This, in turn, lowers the cost of information acquisition and enhances stakeholder monitoring power (Fang et al., 2022). Additionally, digital tools enable board members to promptly analyze key performance indicators, leading to more informed and timely decision-making (Farrokhi et al., 2020). They also improve auditing processes and support more effective risk management practices (Teichmann et al., 2023).

In a recent study on Chinese firms, Yang et al. (2024a) highlight that a high digitalization level led to an improved corporate governance framework by boosting innovation capabilities and reducing information asymmetry. Li et al. (2024) assert that digital technologies transform governance by facilitating process-oriented behavioral monitoring and decreasing reliance on outcome-based incentive systems. Social media platforms expand the scope of information dissemination and governance capacity, while digital tools make it easier to collect customer feedback—allowing firms to develop more competitive products that meet consumers’ expectations. However, when the level of digitalization diverges from a firm's strategic direction, further advancements in digitalization may fail to generate technological benefits, particularly in enhancing communication quality. In such cases, the associated costs may begin to outweigh the benefits, thereby diminishing the positive impact of digitalization on governance performance. Grounded in these insights, we propose the following hypothesis:

Hypothesis 3: There is an inverse U-shaped relationship between digital maturity and corporate governance performance.

3. Data and Methodology

3.1. Data Sample

Our data sample consists of 49 non-financial companies listed on the BIST 100 Index and having the ESG scores for the period of 2016-2022. This timeframe is deliberately chosen as the companies were required to prepare their financial statements according to the inflation accounting application that entered into force by December 31, 2023. Out of the 49 firms in the sample, 33 of them are in the manufacturing industry, while 16 of them are in the service industry. The sectoral categorization of the firms is provided in Table A1 in the Appendix. We excluded firms with less than 3 years of observation data from the sample. We conducted the panel data analysis with 246 observations. It is worth noting that this data accounts for 37.82% of the total market capitalization of the non-financial firms listed on the BIST ALL Index, providing a high

level of representation. We extracted data from multiple sources, i.e. Public Disclosure Platform, Thomson Reuters EIKON database, and corporate annual reports.

3.2. Variables Measurement

Dependent Variable

We used corporate sustainability performance (CSP) as the dependent variable and utilized ESG scores to quantify the CSP. Thomson Reuters DataStream provides the ESG scores of firms. The environmental pillar score (Escore) measures the firm's environmental performance, the social pillar score (Sscore) reflects its social performance, and the governance pillar score (Cscore) assesses its corporate governance performance.

Independent Variable

We used calculated digital maturity (DM) as the independent variable. It quantifies the extent to which firms leverage digital transformation to enhance customer interactions, streamline operational processes, and transform business models (Hess et al., 2020). Research on quantifying DM is limited, largely due to its complexity as a firm-wide strategic transformation, making it challenging to measure (Libert et al., 2016; Gurbaxani and Dunkle, 2019). Following the relevant literature (Guo and Xu, 2021; Wu et al., 2021; Zeng et al., 2022; Su et al., 2023; Fu and Li, 2023), we applied a text mining technique to the annual reports of the firms to measure the DM. We employed MAXQDA to analyze the frequencies of the digital maturity-related keywords in the annual reports (Marjaei et al., 2019).

Based on the extensive literature review and the interviews held with the nine domain experts, we first selected 223 keywords for different levels of digital orientation in firms to construct a digital scale. Then, we processed the annual reports and calculated the frequency of the keywords by using MAXQDA software. As a last step, we normalized the keyword frequencies by dividing by the total number of pages in each report, facilitating comparisons across firms regardless of document length. The selected keywords are given in Table 1.

Table 1. The Selected Keywords Used in The Calculation of The Digital Maturity Scores

Intranet, Internet, Server, Network Infrastructure
Smart TV, Smartphone, Mobility, Internet Access, Network Coverage, Network Function, Network Map
Network Security, Information Security, Digitization, Transformation, Fiber Optic, Broadband, Quick Adaptation, Decision Making, Mobile Device, Performance Management System
Agile, Network Automation, Smart Solutions, Smart Technology, Smart Manufacturing, Data Analytics, Cloud Computing, Cloud Security, Data Privacy, Data Lake, Digital Twin, Digital Business, Digital Workforce, 5G, Optimization, Automation, Robot, Cyber Security, Innovation, Edge Computing
Artificial Intelligence, Big Data, Deep Learning, Smart Factory, Smart Agriculture, Augmented Reality, Blockchain, Business Intelligence, Digital Transformation, Image Recognition, Internet of Things, Machine Learning, Metaverse, Robotic Process Automation, Virtual Factory, Virtual Reality, Sentiment Analysis

The annual report is a formal document in which listed firms publicly disclose their financial performance for the fiscal year. It provides insights into the firm's strategic decisions

and outlook. If a firm has significant strategic shifts, these changes should be clearly disclosed in the annual report. Given the public nature of this report, entities are expected to disclose relevant information about their progress in digitalization in the annual report for ensuring transparency, building trust, and providing stakeholders with a comprehensive understanding of how a firm positions itself for future growth in an increasingly digital world (Chen et al., 2024).

Control Variables

To avoid the potential impact of other factors on CSP, we used firm profitability (Fprofit), firm size (Fsize), firm risk (Frisk), firm age (Fage) and industry as control variables. We picked up the return on assets (ROA) to calculate firm profitability. It was measured by dividing net income to total assets. Firm size was calculated by taking the natural logarithm of the firm’s total assets. Firm risk was measured by dividing total liabilities to total assets. Firm age shows the period since the company was founded and is included in the model by taking its natural logarithm. Industry was used as a dummy variable. It takes the value of “1” for service industry and “0” for manufacturing industry.

3.3. Methodology

To assess the effect of DM on CSP, we conducted panel regression analysis using Stata. A dummy variable is incorporated for each year to capture anything unique to the selected period. We first estimated Equation 1 as a baseline regression model. To provide evidence for a U-shaped relationship, we regress CSP on DM and its square DM^2 in Equation 2. A significant and negative coefficient for DM^2 indicates an inverted U-shaped relationship, whereas a significant and positive coefficient for DM^2 shows a U-shaped relationship (Haans et al., 2016).

$$CSP_{i,t} = \alpha + \beta_1 DM_{i,t} + \beta_2 Fprofit_{i,t} + \beta_3 Fsize_{i,t} + \beta_4 Flev_{i,t} + \beta_5 Fage_{i,t} + \beta_6 Industry_{i,t} + \sum_{k=1}^7 \lambda_k Year + e_{i,t} \quad (1)$$

$$CSP_{i,t} = \alpha + \beta_1 DM_{i,t} + \beta_2 DM_{i,t}^2 + \beta_3 Fprofit_{i,t} + \beta_4 Fsize_{i,t} + \beta_5 Flev_{i,t} + \beta_6 Fage_{i,t} + \beta_7 Industry_{i,t} + \sum_{k=1}^7 \lambda_k Year + e_{i,t} \quad (2)$$

4. Empirical Findings

4.1. Descriptive Statistics

Table 2 reports the summary of the descriptive statistics, while Table 3 shows the correlation matrix. The mean score of Escore is 59.452 with a standard deviation of 25.131, showing that the Escore varies among firms in the sample. This variable also exhibits a significant positive correlation of 0.371 with DM, indicating that as DM increases, the degree of digital adaptation significantly contributes to Escore. The Score has a mean of 67.025 and a standard deviation of 24.237. There exists a significant positive correlation of 0.422 with DM, implying that firms with higher social scores are likely to have a higher digitalization level. Concurrently, the Cscore exhibits a mean of 53.938 and a standard deviation of 21.888. It correlates positively

with DM, denoted by a coefficient of 0.215. The average DM score is only 2.406, with a maximum score of 10.905, highlighting significant variations in the level of digitalization among the Turkish firms. For firm size and firm risk, a significant positive correlation is noted with the ESG scores, whereas a significant positive correlation is observed with firm age only for Escore. The VIF values for the explanatory variables are less than 10, indicating that multicollinearity is unlikely to affect our results.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Escore	246	59.452	25.131	0	98.88
Sscore	246	67.025	24.237	.8	97.2
Cscore	246	53.938	21.888	1.81	90.8
DM	246	2.406	1.902	.083	10.905
Fprofit	246	.077	.081	-.193	.396
Fsize	246	16.443	1.194	13.899	20.176
Frisk	246	.613	.213	.063	1.019
Fage	246	3.726	.422	2.639	4.489
Industry	246	.333	.472	0	1

Table 3. Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Escore	1.000								
(2) Sscore	0.813*	1.000							
(3) Cscore	0.492*	0.523*	1.000						
(4) DM	0.371*	0.422*	0.215*	1.000					
(5) Fprofit	-0.019	-0.032	0.000	0.108	1.000				
(6) Fsize	0.345*	0.298*	0.302*	0.090	-0.016	1.000			
(7) Frisk	0.248*	0.348*	0.235*	0.225*	-0.420*	-0.022	1.000		
(8) Fage	0.153*	0.079	-0.037	-0.015	0.052	0.182*	-0.107	1.000	
(9) Industry	-0.140*	-0.023	0.058	0.131*	-0.235*	0.136*	0.315*	-0.342*	1.000

Note: * p<0.05

4.2. Estimation Results

Using the ESG scores, we run an unbalanced panel data analysis. Given that all values of the dependent variable in our analysis are non-zero, we used linear regression, i.e., ordinary least squares (OLS), to model the relationship between DM and CSP. Figure 1 displays the scatter plot with fitted lines depicting the relationship between these variables. The red line represents the quadratic fit for the relationship between DM and CSP. We first estimated a fixed effects regression model and conducted an F-test to determine if any firm-specific attributes were present. The results indicated that a pooled OLS model was not appropriate. We then conducted a Hausman (1978) test to determine the most suitable model for the data. The result indicated that for all dependent variables, the random effects model is better. Table 4 reports the results. According to the baseline regression results (Model 1a, 2a, and 3a), we could not identify a linear relationship between DM and Escore, Sscore and Cscore.

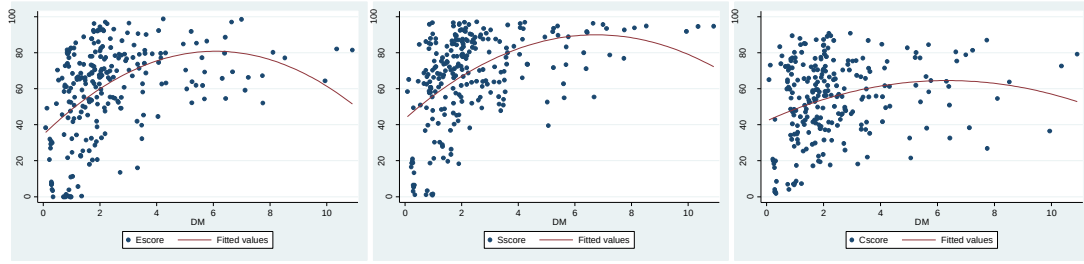


Figure 1. The Fitting Diagram of the Digital Maturity Level and ESG Scores

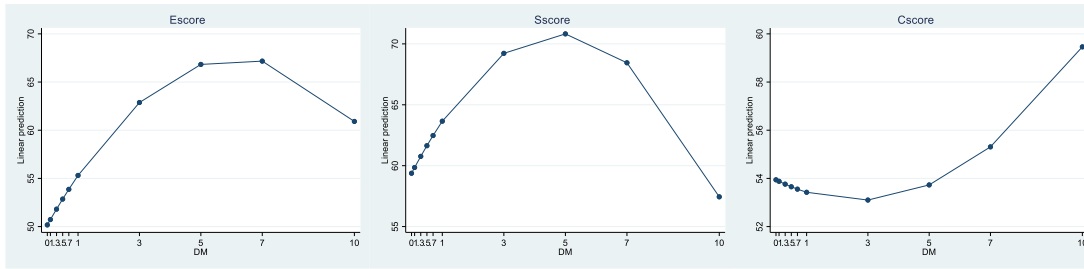


Figure 2. The Non-Linear Relationship Between Digital Maturity Level and ESG Scores

Table 4. Panel Data Analysis Results

Variables	(1a) Escore	(1b) Escore	(2a) Sscore	(2b) Sscore	(3a) Cscore	(3b) Cscore
DM	1.658 (0.948)	5.589* (2.307)	0.477 (0.704)	4.772** (1.333)	0.359 (0.980)	-0.637 (3.003)
DMsq		-0.451 (0.251)		-0.497** (0.116)		0.119 (0.313)
Fprofit	35.833 (24.977)	41.935 (25.103)	12.292 (20.987)	18.849 (20.643)	36.724 (25.654)	35.436 (24.671)
Fsize	6.806** (1.775)	6.821** (1.717)	5.358** (1.844)	5.384** (1.781)	4.484* (1.964)	4.543* (1.971)
Frisk	25.086 (15.443)	22.187 (14.970)	29.729 (15.948)	25.814 (15.251)	22.118 (14.957)	23.445 (14.823)
Fage	-1.434 (9.028)	-1.009 (8.875)	-6.052 (9.005)	-5.380 (8.774)	-6.584 (6.635)	-6.631 (6.610)
Industry	-12.676 (7.886)	-11.106 (7.626)	-10.792 (8.182)	-8.876 (8.123)	-4.019 (5.965)	-4.517 (6.114)
Constant	-70.455 (39.849)	-75.485 (38.989)	-28.338 (37.445)	-34.375 (36.171)	-12.396 (34.221)	-12.626 (34.638)
Observations	246	246	246	246	246	246
Number of firms	49	49	49	49	49	49
Lind and Mehlum (2010) utest						
Overall utest		1.23 (0.111)		3.56 ** (0.000)		0.21 (0.417)
Lower bound slope		2.429 ** (0.007)		3.561 ** (0.000)		-0.208 (0.417)
Upper bound slope		-1.225 (0.110)		-3.831 ** (0.000)		0.475 (0.317)
Extreme point		6.18		4.80		2.67

Note: Numbers in parentheses are standard errors, except for Lind and Mehlum (2010) utest, which are p-values. ** p<0.01 * p<0.05

Figure 2 shows the relationship between DM and CSP. As DM increases from 0 to 5, environmental performance improves. This suggests that firms that become more digitally mature tend to adopt practices that enhance environmental performance through more efficient resource use, better data tracking, and sustainability-focused innovations. Between DM 5 and 7, the performance gain slows down and reaches a peak (DM= 6.18), implying diminishing returns — increasing digital maturity still helps, but not as dramatically. After DM 7, environmental performance declines. Over-digitalization might introduce complexity. Although Figure 2 shows an inverted U-shaped relationship between DM and environmental performance, the regression results did not fully support this finding (Table 4, Model 1b). In Model 1b, the linear term is significant and positively ($\beta = 5.589$, $p < 0.05$) associated with Escore, but the squared term of DM is insignificant and negatively ($\beta = -0.451$, $p > 0.10$) associated with Escore. Following Haans et al. (2016) and Lind and Mehlum (2010), we applied "utest". In Model 1b, the slope for the lower bound is 2.429 ($p < 0.01$), indicating that the relationship between Escore and DM is positive and significant, whereas the slope for the upper bound is -1.225 ($p > 0.10$), showing that the same relationship is negative and insignificant. The overall test for the existence of a U-shaped relationship for Escore yields a t-value of 1.23 and a corresponding p-value of 0.111, suggesting that the null hypothesis is accepted, and the relationship is not inverse U-shaped. This finding partially supports Hypothesis 1. From the RBV perspective, the results show that firms improve environmental performance by implementing digital technologies. However, an intense level of digitalization in advanced stages may have its own environmental impact, i.e., high energy consumption and pollution, e-waste, which diminishes its positive effect on environmental performance. Although the result is not significant, it indicates that there is a rebound effect and corroborates the findings of prior studies (Ahmadova et al., 2022; Chen and Hao, 2022; Li, 2022).

The result for the DM in Model 2b satisfies the fundamental criteria for an inverse U-shaped relationship. The nonlinear relationship between the Sscore and DM is shown in Figure 2. The linear term is positively ($\beta = 4.772$, $p < 0.01$) and the squared term of DM is negatively ($\beta = -0.497$, $p < 0.01$) associated with the Sscore. The overall test for the existence of a U-shaped relationship for Sscore yields a t-value of 3.56 and a corresponding p-value of 0.000, suggesting that the null hypothesis is rejected, and the relationship is inverse U-shaped. In Model 2b, the slope for the lower interval is 3.561 ($p < 0.01$), indicating that the relationship between Sscore and DM is positive and significant. On the other hand, the slope for the upper interval is -3.831 ($p < 0.01$), implying that the same relationship becomes negative and significant. When DML is higher than the threshold of 4.80, it corresponds to a lower Sscore, whereas when it is lower than 4.80, it corresponds to a better Sscore. This finding supports Hypothesis 2. The results suggest that while early-stage digitalization enhances social performance by promoting transparency, stakeholder engagement, and workforce well-being, directly aligning with the expectations of internal and external stakeholders, a higher level of digitalization may shift the focus toward operational efficiency, potentially reducing emphasis on social considerations. This shift is further compounded by the risks associated with excessive reliance on digital technologies, which, despite boosting efficiency, can lead to job losses (Khogali and Mekid, 2023), decreased employee satisfaction (Mettler, 2024), and ethical concerns such as surveillance and biased artificial intelligence decisions (De Stefano, 2020). This transition may create tensions with stakeholder interests, erode stakeholder trust, and signal a reduced organizational responsiveness, which stakeholder theory identifies as detrimental to long-term sustainability.

In Model 3b, the linear term is negatively ($\beta = -0.637$, $p > 0.10$) and the squared term of digital maturity is positively ($\beta = 0.119$, $p > 0.10$) associated with the Cscore, but they are all insignificant. This finding does not support Hypothesis 3. It reflects the lag in corporate governance relative to digital technological capabilities among Turkish firms and inherent implementation challenges in corporate governance structures. These challenges may include management hierarchy restructuring, workforce displacement, and process redundancies.

In Table 4, in all Models, Fsize has a positive and significant effect on sustainability pillars. Larger firms typically have more resources, enabling them to invest in ESG initiatives more effectively. This advantage allows them to implement and support comprehensive ESG strategies that align with stakeholder expectations. Moreover, they should assume more social responsibility in managing the pressures of stakeholders (Bissoondoyal-Bheenick et al., 2023).

4.3. The Robustness Tests

To mitigate the issue of reverse causality, this study incorporates lagged variables of digital maturity into the regression model, specifically lagging them by one period. As shown in Table 5, the results from the lagged model align with those of the original model, suggesting that the findings are robust and not influenced by endogeneity arising from reverse causation. Moreover, we conducted another robustness check to account for the impact of COVID-19 by including a time dummy variable (Covid19)—set to 1 for the year 2020 and 0 otherwise—in the regression, as shown in Table 6. The coefficients of the interaction terms (DMxCovid19 and DMsqxCovid19) are insignificant, indicating that the relationship between DM and CSP has not changed during the COVID-19 period.

Table 5. Panel Data Analysis Results (Lagged Variables Of DM)

Variables	(1) Escore	(2) Sscore	(3) Cscore
L_DM	5.607* (2.717)	3.147* (1.476)	-2.156 (3.739)
L_DMsq	-0.465 (0.320)	-0.346** (0.131)	0.312 (0.412)
Fprofit	40.140 (23.048)	22.080 (19.169)	27.261 (25.004)
Fsize	5.911** (1.677)	4.939** (1.788)	4.722* (1.909)
Frisk	18.750 (15.837)	31.359 (16.176)	22.337 (16.362)
Fage	1.240 (9.233)	-2.553 (9.458)	-6.667 (6.785)
Industry	-8.664 (8.067)	-7.892 (8.843)	-4.061 (6.203)
Constant	-65.328 (42.412)	-36.078 (40.183)	-8.903 (36.341)
Observations	196	196	196
Number of HisseID	49	49	49

Note: Numbers in parentheses are standard errors** $p < 0.01$ * $p < 0.05$

Table 6. Panel Data Analysis Results (Covid19)

Variables	(1) Escore	(2) Sscore	(3) Cscore
DM	5.454* (2.496)	4.748** (1.311)	-1.688 (3.353)
Covid19	5.874 (6.098)	14.499* (6.038)	-3.705 (5.788)
DMxCovid19	0.576 (1.897)	-0.008 (1.681)	4.649 (2.700)
DMsq	-0.430 (0.272)	-0.493** (0.121)	0.248 (0.364)
Covid19	-	-	-
DMsqxCovid19	-0.137 (0.178)	-0.041 (0.157)	-0.615* (0.273)
Fprofit	41.516 (25.303)	18.411 (20.969)	32.792 (24.738)
Fsize	6.999** (1.761)	5.547** (1.776)	4.674* (1.976)
Frisk	21.125 (15.262)	24.627 (15.424)	23.732 (14.960)
Fage	-1.477 (8.881)	-5.881 (8.713)	-7.038 (6.574)
Industry	-10.985 (7.624)	-8.801 (8.120)	-4.810 (6.129)
Constant	-74.879 (39.263)	-33.722 (36.364)	-11.641 (34.793)
Observations	247	247	247
Number of HisseID	49	49	49

Note: Numbers in parentheses are standard error ** p<0.01 * p<0.05

5. Discussions

This study was conducted during a period when emerging market firms are experiencing intense pressure to undergo digital transformation. However, before fully embracing digitalization, companies must carefully consider its potential implications for ESG performance. Unlike many prior studies, this research brings a nonlinear relationship between digitalization and ESG performance into the discussion. Empirical findings reveal that while digitalization initially enhances social performance, its benefits diminish beyond a certain threshold—ultimately resulting in a negative impact. The identified inverted U-shaped relationship between digital maturity and social performance suggests that excessive reliance on automated systems for managing social interactions can undermine human-centered approaches essential for effective social engagement. Moreover, highly digitalized firms may face challenges in maintaining meaningful personal connections with customers, employees, and communities, potentially leading to a sense of detachment and reduced ability to meet evolving social expectations.

The results show a similar inverse U-shaped but insignificant relationship between digital maturity and environmental performance. On one side, digital transformation positively contributes to environmental performance through operational efficiency, while on the other hand, digitalization can be energy-intensive and can lead to increased emissions and energy consumption. However, it is important to note that the relationship might vary when considering different types of technologies due to their distinct environmental effects.

Although digital transformation significantly influences corporate governance and offers substantial benefits when digital technologies are integrated into governance structures, the observed insignificant relationship between digital maturity and corporate governance suggests that integrating digitalization into existing governance frameworks is not straightforward. Several factors contribute to this complexity. First, corporate governance must evolve rapidly to keep pace with technological advancements. However, this transition is demanding, as it often requires replacing or upskilling existing talent and making a significant investment (Sama et al., 2022). Second, as firms digitize their operations, they become increasingly vulnerable to cybersecurity threats—raising concerns over data breaches and the protection of sensitive information, which can seriously undermine corporate governance (Magnusson and Blume, 2022). Lastly, implementing digital governance necessitates a fundamental shift in mindset. Firms must foster a culture of continuous learning and digital literacy, which may face internal resistance and require active change management.

5.1. Theoretical and Practical Implications

5.1.1. Theoretical Implications

This study offers important theoretical implications and contributes to the growing body of literature on the relationship between digital maturity and corporate sustainability performance. It deepens the understanding of the drivers of sustainability performance by examining the impact of firm-level digital transformation through the lens of stakeholder theory and resource-based view. Our findings highlight the critical role of digitalization in influencing a firm's sustainability performance. They provide new evidence on how firms in emerging markets operating within an increasingly digital ecosystem, should align their strategies with stakeholder theory by structuring better mechanisms for transparency, stakeholder engagement, and collaboration. From a resource-based view, the results further suggest that digital maturity functions as a strategic resource, enhancing a firm's ability to reduce operational inefficiencies, promote cross-departmental collaboration, and achieve sustainable outcomes. These include improved resource optimization, lower emissions, and the development of more sustainable products.

5.1.2. Practical Implications

This study offers valuable insights for companies and policymakers, particularly in the context of emerging markets, where corporate sustainability performance holds significant importance. The results imply that while digital transformation may initially bring improvements that positively influence environmental and social performance, it is important to consider its potential negative consequences that may arise over time. This dual role of digital transformation, both enabling and disrupting, requires adaptive management strategies to maximize its benefits. Therefore, firms should adopt a long-term strategy that integrates digitalization and ESG performance, taking deliberate actions to align technological advancements with social and environmental outcomes. To support this integration, companies should invest in developing digital expertise to ensure that employees possess the necessary digital skills to drive sustainability initiatives. On the other hand, to strengthen the link between digital transformation and corporate governance, managers should leverage advanced digital tools to enhance decision-making and streamline management processes, thereby improving both operational and financial

performance. However, they must also remain aware of the potential challenges to ESG performance that can emerge at higher levels of digitalization. In this respect, our findings provide strong evidence of rebound effects —where the unintended consequences of advanced digitalization may offset earlier gains. Awareness of this risk can help managers design more effective policies and practices to mitigate negative impacts. This issue is particularly important for emerging market firms that often operate within relatively weak institutional frameworks. These firms should be conscious of their environmental footprint and implement sustainability-driven social policies to reduce the adverse impacts of digitalization.

For policymakers, the findings highlight the need to increase support for digital transformation initiatives while ensuring that ESG performance discrepancies are effectively addressed. In this respect, developing a comprehensive and strategic approach to digital transformation is essential. Policymakers should enact forward-looking policies that promote the adoption of digital technologies, support firms in implementing data-driven social and environmental strategies, and progressively integrate ESG indicators into corporate performance assessments. Each sector should have its own policy framework adjustments that can help firms to optimize their digital transition while sustaining environmental and social performance. In this frame, governments should establish a robust policy framework that aligns digital transformation with the pillars of sustainability, with a particular focus on ESG data integration and technological convergence across industries. Additionally, regulators should further encourage ESG disclosure and enhance oversight mechanisms to ensure transparency and accountability. They should motivate more companies to voluntarily report their digitalization and sustainability performance, thereby fostering a culture of responsible and transparent corporate behavior.

5.2. Limitations and Future Research

This study has several limitations that present avenues for future exploration. First, the sample is limited to listed companies, as data on digitalization and ESG pillars are more readily available for these firms. Future research could be conducted in specific industries to provide deeper insights and explore the contribution of different digital technologies to ESG performance. Second, our analysis focuses solely on Turkish companies. This geographic limitation may affect the generalizability of the findings, given the differences in institutional frameworks, culture, and digital capabilities across emerging markets. Future studies may expand the scope of analysis by conducting cross-country comparisons to validate and complement our findings. Third, this study does not include any moderating and mediating variables that could further illuminate the relationship between digital maturity and sustainability performance. Future research may benefit from incorporating such variables to obtain more nuanced and refined results. This could involve investigating contextual factors that influence the effectiveness of digital technology interventions in driving sustainability outcomes. Finally, it is important to acknowledge the limited availability of digitalization-related information in companies' annual reports, largely due to corporate confidentiality. To address this constraint, future studies could collect primary data through surveys and interviews, thereby enhancing the robustness and validity of the conclusions. Moreover, the development of sector-specific dictionaries to measure digital operations could help refine our methodology and discover the unique effects of digital transformation on ESG pillars.

6. Conclusions

Given the rapid evolution of information technologies, digitalization has become a key driver for companies aiming to improve sustainability performance across their business activities. The adoption of digital technologies offers a competitive advantage by reducing costs, increasing quality, and enabling differentiated market positioning. However, despite these benefits, a high level of digitalization may also pose challenges for ESG performance. This study explores the impact of digital maturity on corporate sustainability performance by conducting a text mining analysis of the annual reports of 49 non-financial firms listed on Borsa Istanbul, covering the period from 2016 to 2022.

The results reveal that the relationship between digital maturity and social performance follows a curvilinear pattern, characterized by an inverted U-shaped curve. While digital orientation initially enhances social performance, excessive digitalization may lead to organizational conflicts and increased costs, thereby diminishing these benefits. Regarding environmental performance, although the regression analysis identifies an inverted U-shaped relationship with digital maturity, the result is not significant. The analysis reveals different levels of significance at the lower and upper bounds of digital maturity. At lower levels, an increase in digital maturity is associated with improved environmental performance — indicating that as firms begin to digitize, they experience meaningful gains in managing environmental issues. This is reflected in a positive and statistically significant slope at the lower bound. Conversely, at higher levels of digital maturity, further increases in digitalization do not lead to additional improvements in environmental performance and may even slightly reduce it, although this negative slope is not statistically significant. This may stem from the fact that digitalization can be energy-intensive and can lead to an increase in growth-led emissions. Finally, the results did not produce evidence of a nonlinear relationship between digital maturity and corporate governance performance.

The findings contribute to a deeper understanding of sustainability performance in emerging markets, providing valuable insights for the development and execution of effective ESG strategies in the digital age. Firms should pursue balanced and well-considered digitalization policies, as excessively high levels of digitalization may negatively influence social and environmental dimensions. To leverage digital technologies for improved sustainability outcomes, firms must invest in skilled human capital, ensure adequate training, and optimize resource usage. Rather than blindly pursuing digital transformation, firms must focus on building the digital capabilities of both management and employees. Strengthening this digital capacity is essential for achieving meaningful and long-lasting improvements in sustainability performance.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There are no potential conflicts of interest in this study.

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APPENDIX

Table A1. The Sample

Service Sector Firms (n=16)	Sub-sectors	Manufacturing Sector Firms (n=33)	Sub-sectors
AKENERJİ ELEKTRİK ÜRETİM	Electricity	AKCANSAN CİMENTO SANVETC.	Others
AKSA ENERJİ ÜRETİM	Electricity	AKSA AKRİLİK KİMYA ŞYİ.	Others
BİM BİRLİK MAGAZALAR	Food and Drug Retailers	ANADOLU EFES BİRACILIK LTD.	Beverages
BİZİM TOPTAN SATIŞ MAGAZA.LTD.	Food and Drug Retailers	ARCELİK	Household Goods and Home Construction
DOĞUS OTOSERVİS VTC.	General Retailers	ASELSAN ELNKSANVETC.	Aerospace and Defense
ENERJİSA ENERJİ	Electricity	AYGAZ	Gas, Water and Multiutilities
ENKA İNŞAAT VE SANAYİ A	Construction and Materials	BRİSA BDGSN.SLK.SANVETC.	Automobiles and Parts
MAVİ GİYİM SANAYİ VE TİCARET	General Retailers	CİMSA CİMENTO SANVETC.	Others
MİGROS TİCARET	Food and Drug Retailers	COCA COLA İÇECEK	Beverages
MLP SAĞLIK HİZMETLERİ	Health Care Equipment and Services	EİS ECZACİBAŞI İLLAC SİNAYİ VE FİAL.YATIRIMLAR	Pharmaceuticals and Biotechnology
PEGASUS HAVA TAŞIMACILIĞI A LTD.	Travel and Leisure	EREĞLİ DEMİR ÇELİK	Industrial Metals and Mining
SELÇUK ECZA DEPOSU	Pharmaceuticals and Biotechnology	FORD OTOMOTİV SANAYİ	Automobiles and Parts
SOK MARKETLER TİCARET	Food and Drug Retailers	İSKENDERUN DEMİR	Industrial Metals and Mining
TÜRK HAVA YOLLARI	Travel and Leisure	KARŞAN OMV.SANVETC.	Automobiles and Parts
TÜRKCELL İLETİŞİM HİZM.	Fixed Line Telecommunications	KEREVİTAS GIDA SANVETC.	Food Producers
ZORLU ENERJİ	Electricity	KORDSA TEKNİK TEKSTİL A	Others
		KOZA ALTIN İŞLETMELERİ	Mining
		KOZA ANADOLU MTL.MİE.	Others
		LOGO YAZLIM	Software and Computer Services
		NORTEL NETWORKS.NETAS TKS.	Technology Hardware and Equipment
		OTOKAR OMV.VE SAVUNMA	Industrial Engineering
		PETKİM PETROKİMYA HİLDG.	Chemicals
		PETUN ET VE İN	Food Producers
		PİNAR SUT MAMÜLLERİ ŞYİ.	Food Producers
		SASA POLYESTER A	Others
		TAT GIDA SANAYİ	Food Producers
		TAV HAVALİMANLARI	Industrial Transportation
		TOFAS TÜRK OTOM.FABK.	Automobiles and Parts
		TUPRAS TKİ.PEL.RFNE.	Others
		TÜRK TKTR.VE ZİRAAT MKE.	Others
		ÜLKER BİSKÜVİ SANAYİ	Food Producers
		VESTEL BEYAZ EŞYASANVETC.	Leisure Goods
		VESTEL ELNKSANVETC.	Leisure Goods

DRIVERS OF CO₂ EMISSIONS: EVIDENCE FROM BANKING, DIGITALIZATION, AND RESOURCE DEPLETION*

CO₂ Emisyonlarının Belirleyicileri: Bankacılık, Dijitalleşme ve Doğal Kaynak Tükenmesinden Bulgular

Alper AKPINAR** & Gül HUYUGÜZEL KİŞLA***

Abstract

This study analyzes the environmental impacts of banking, digitalization, and natural resource depletion in line with sustainable development goals for 94 countries covering the period 2014-2021. For this purpose, index values for banking and digitalization variables were generated using principal component analysis (PCA). Subsequently, econometric analysis was conducted using quantile regression and the IV-2SLS method as a supplementary method, considering the heterogeneous nature of carbon emissions. The findings reveal that digitalization and natural resource depletion increase carbon emissions at every quantile. The increasing carbon emissions impact of digitalization points to a rebound effect, which has recently gained support in the literature. The IV-2SLS findings also support these findings. However, as carbon emissions reach higher quantiles, the effects of digitalization decrease, while the effects of natural resource depletion increase. While banking initially has a reducing effect on carbon emissions, its effect appears to become insignificant as carbon emissions reach higher quantiles. The IV-2SLS findings, however, reveal a negative relationship for the overall panel. This suggests that the banking variable has different effects on carbon emissions for different emission levels. Considering the findings, we contribute to the literature by presenting important policy recommendations that are consistent and complementary to the findings.

Öz

Bu çalışma, 2014-2021 dönemi ve 94 ülke için sürdürülebilir kalkınma hedefleri doğrultusunda bankacılık, dijitalleşme ve doğal kaynak tükenmesinin çevresel etkilerini analiz etmektedir. Bu amaçla, bankacılık ve dijitalleşme değişkenlerine ait endeks değerleri temel bileşen analizi (PCA) kullanılarak üretilmiştir. Daha sonra, karbon emisyonlarının heterojen yapısı göz önünde bulundurularak, kantil regresyon ve tamamlayıcı yöntem olarak IV-2SLS yöntemi kullanılarak ekonometrik analiz gerçekleştirilmiştir. Bulgular, dijitalleşme ve doğal kaynak tükenmesinin her kantilde karbon emisyonunu artırdığını ortaya koymaktadır. Dijitalleşmenin karbon emisyonlarını artırdığına ilişkin bulgular, son zamanlarda literatürde destek kazanan rebound etkisine işaret etmektedir. IV-2SLS bulguları da bu bulguları desteklemektedir. Bunun yanı sıra, karbon emisyonlarının düzeyi arttıkça, dijitalleşmenin etkileri azalırken, doğal kaynak tükenmesinin etkileri artmaktadır. Bankacılık başlangıçta karbon emisyonları üzerinde azaltıcı bir etkiye sahipken, karbon emisyonları daha yüksek kantillere ulaştıkça bu etkinin istatistiksel olarak anlamsızlaştığı görülmektedir. Ancak IV-2SLS bulguları, genel panel için negatif bir ilişki ortaya koymaktadır. Bu, bankacılık değişkeninin farklı emisyon seviyeleri için karbon emisyonları üzerinde farklı etkilere sahip olduğunu göstermektedir. Bulguları göz önünde bulundurularak, bulgularla tutarlı ve tamamlayıcı nitelikte önemli politika önerileri sunarak literatüre katkıda bulunuyoruz.

Keywords:

Sustainable Development, Carbon Emissions, Banking, Digitalization, Natural Resource Depletion

JEL Codes:

Q01, Q53, G21, O39, Q34.

Anahtar

Kelimeler:

Sürdürülebilir Kalkınma, CO₂ Emisyonları, Bankacılık, Dijitalleşme, Doğal Kaynak Tükenmesi

JEL Kodları:

Q01, Q53, G21, O39, Q34.

* This study is based on the doctoral thesis, “Banking and Digitalization in Line with Sustainable Development Goals” currently being conducted at Ege University.

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1. Introduction

Digitalization, which entered our lives in the 21st century and has recently attracted increasing attention, is a process that deserves careful attention in terms of sustainable development goals. Undoubtedly, the spread of digital transformation and its increasing presence in our lives are changing our patterns of both production and consumption. However, this process also has a dynamic that increases our energy demand. Along with increasing energy demand, the ever-growing information and communication technologies sector and data centers are solely responsible for approximately 1.5-3.2% of CO₂ emissions, according to 2020 data (UNCTAD, 2024). Add to this the rapidly developing and growing artificial intelligence technologies of the past few years, and it seems inevitable that these rates will increase unless measures are taken. On the other hand, approaches that prioritize energy efficiency by expanding green innovation can help reduce CO₂ emissions (Zhang et al., 2024). However, due to rising energy demands and the increasing energy use in the sector, measures that can be taken can only slow growth and, unless sustained, will not contribute to the long term (Axenbeck et al., 2024). Therefore, careful examination of the impacts of digitalization on CO₂ is a critical issue.

The banking sector is both subject to digital transformation and, due to its market funding power, has the capacity to price environmental risks. Altavilla et al. (2024) observe that banks in the Eurozone internalize environmental risks, consequently granting higher interest rates to projects with higher risks. Nevertheless, low CO₂ commitments are typically voluntary. Large banking institutions have been observed to occasionally neglect the internalization of environmental risks, with the primary objective being the maximization of short-term profits. This approach is undertaken to provide market flexibility by circumventing the monitoring of risks that have been internalized (Sastry et al., 2024). Nevertheless, it is noteworthy that the banking sector is increasingly pricing environmental risks (Ho and Wang, 2023). In consideration of the fact that, in addition to digitalization, access to credit financing has become more straightforward thanks to digital technologies, and the banking sector has become more widespread, the impact on CO₂ is worthy of examination.

Natural resources have a significant multiplier effect on CO₂ emissions, both through their extraction and use. In particular, resource-dependent countries' climate goals conflict with their production structures (International Resource Panel, 2024). Ignoring environmental impacts in the pricing process of natural resources reduces the costs of these resources, accelerates natural resource depletion by increasing demand and consumption, and increases environmental risks (World Bank, 2021). Therefore, natural resource depletion poses a significant risk to climate goals due to both the reluctance of countries with economies dependent on natural resources to price these risks and the environmental damage caused by exploration, extraction, and production activities.

This study explores the environmental impacts of the uncontrolled and rapid spread of digitalization, a necessity of our times, while also exploring the potential environmental impacts of the banking sector, both through production and consumption behaviors and through credit and intermediation, due to the increased accessibility of the banking sector, due to developing technology, and digitalization. In addition, the ease that digitalization has created in the exploration, extraction, and production of natural resources and the environmental degradation caused by increased production activities resulting from the increased demand for some rare

minerals required for the use of digital technologies are examined together. Similarly, one of the important aims of the study is to understand whether the dominant side of the contradiction experienced by the banking sector, on the one hand, implementing climate targets, and on the other hand, creating financing opportunities for natural resource extraction and production activities in countries dependent on natural resources, is climate targets or resource destruction.

The study contributes to the literature in several areas. First, the digitalization and banking variables were constructed using principal component analysis (PCA) rather than using an indicator variable. Second, the study employs a large sample size and employs an econometric method that takes into account the heterogeneity of the sample. Third, the impacts of banking and digitalization, as well as natural resource depletion, on CO₂ are analyzed. Finally, the model used is unique in the literature. Banking and digitalization indices were generated as independent variables to explain CO₂ emissions, natural resource degradation was included in the model, and renewable and non-renewable energy production and per capita industrial production were used as control variables.

The study consists of four main sections. The first section is the introduction. This section introduces the topic, discusses the variables, explains the importance of the topic, and highlights the unique aspects of the study. The second section explores the theoretical approaches to the study's dependent and independent variables and provides a review of the relevant literature. Furthermore, the conclusion of this section analyzes similar studies in the literature, explains the gaps the study will fill in more detail, and includes the hypotheses the study will test. The third section presents the empirical structure of the study. The dataset and variables used in the study are introduced, references to the variables in the literature are reviewed, the methodology is briefly explained, and the findings are presented and interpreted. Finally, the fourth section is the conclusion, which interprets and discusses the final findings of the study. This section discusses the findings and compares them with similar findings in the literature to reveal their theoretical support. Furthermore, comprehensive policy recommendations aligned with the findings make significant contributions to the literature. Finally, the study concludes with a brief overview of the study's limitations.

2. Theoretical Approaches and Literature

2.1. Review of Carbon Emissions (CO₂)

This section uses a map to examine the distribution of carbon emissions across the sample, revealing the inequity in distribution by calculating the Carbon GINI Index. Figure 1 shows the carbon map for the countries included in the study (see Table A1 for a list of these countries). The presence of grey areas on the map signifies countries that were not included in the study's sample. The data show an increase in per capita carbon emissions from light blue to dark blue. When examining the data covering average per capita carbon emissions between 2014 and 2021, the countries with the highest values are China, Russia, Japan, Germany, and South Korea, respectively. Furthermore, per capita carbon emissions measured in China (average of 11,452 tons from 2014 to 2021) account for approximately 48% of the total emissions in the entire sample. However, the countries with the lowest per capita carbon emissions are Guinea-Bissau, Samoa, Lesotho, Djibouti, and Cabo Verde, respectively. Each of these countries has a per capita carbon emission value below 1%. Consequently, an examination

of Figure 1 reveals that per capita carbon emissions are largely concentrated in Asian countries. However, the lowest values are mostly measured in African countries.

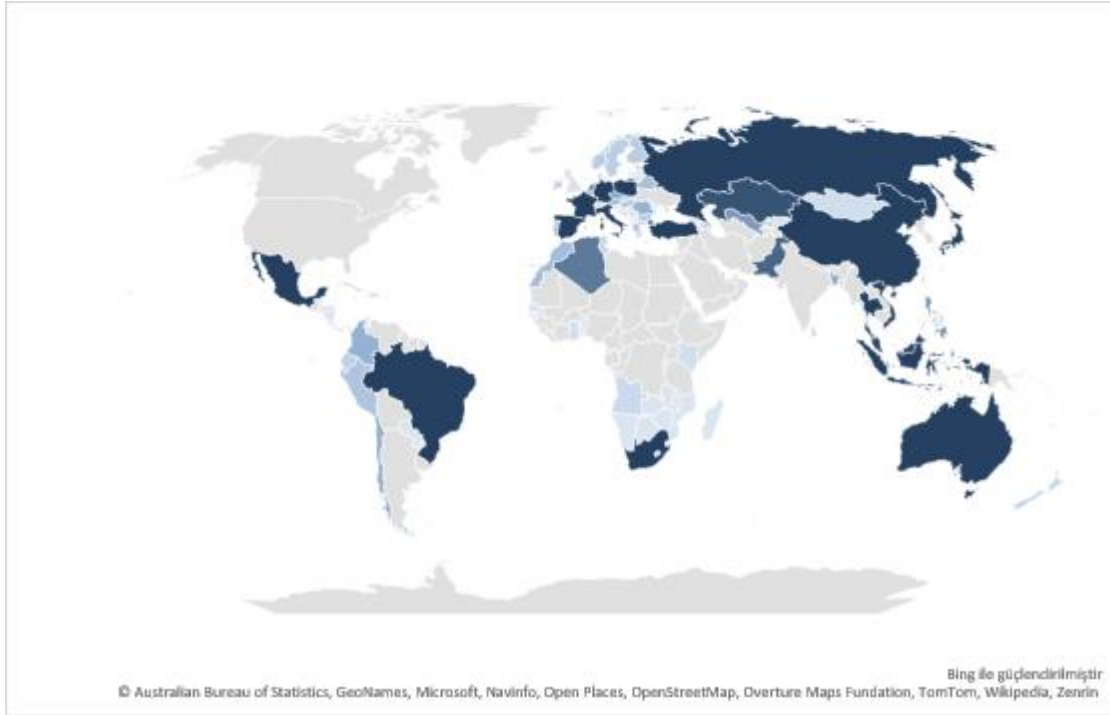


Figure 1. Per Capita Carbon Emission (CO₂) Map
Source: Created by the authors using World Bank data.

Another issue of equal importance to the map in examining per capita carbon emissions is the distribution of carbon emissions. In the literature, the proportion of carbon emissions per capita can be calculated using a method similar to the GINI coefficient. In economics, the GINI coefficient, which measures income distribution equity, measures the percentage share of income received by each 20% of the population (Cowell, 2011). The carbon GINI coefficient can also be calculated in a similar way. Studies such as Teng et al. (2011), Hubacek et al. (2017), Bolea et al. (2020), Zhou et al. (2020), and Chancel et al. (2022) calculate a carbon GINI coefficient similar to the classical GINI coefficient and reveal the inequity of carbon distribution. This index can be calculated using the formula in Equation 1:

$$\text{GINI} = \left(\sum_{i=1}^n \sum_{j=1}^n |x_i - x_j| \right) / (2n^2 \bar{x}) \quad (1)$$

In the GINI equation expressed in Equation 1, x_i represents the carbon emissions of each country, and x_j represents the carbon emissions of other countries. Here, the difference between each country's carbon emission value and the carbon emission values of other countries is taken, and their absolute values are summed. Due to the absolute value, two sum operators are used (Cowell, 2011; Hubacek et al., 2017). The expression n^2 at the bottom of the division operation represents the square of the total number of countries, while $\bar{x}$ represents the average value of carbon emissions. The GINI coefficient obtained with this formula takes a value between 0 and

1. As the value approaches 0, the inequity in the distribution decreases, and as it approaches 1, the inequity in the distribution increases (Cowell, 2011).

Similar to the Lorenz Curve approach described by Cowell (2011), CO₂ emissions can be examined by dividing them into 20th percentiles. Countries in the 2nd percentile with the lowest per capita carbon emissions are responsible for 0.2% of total per capita emissions, while countries in the 40th percentile appear to be responsible for 0.8%. Countries in the 60th percentile are responsible for 2.8% of total per capita carbon emissions, while countries in the 80th percentile are responsible for 8.5%. Finally, countries in the 2nd percentile with the highest per capita carbon emissions appear to be responsible for 87.7% of carbon emissions. These calculated data indicate that countries in the 20th percentile with the highest per capita carbon emissions emit an incomparable difference compared to other countries. The carbon GINI index calculated with Equation 1 also takes the value of 0.846, supporting these data. This value, which is extremely close to 1 in the 0-1 range, reveals that the distribution of carbon emissions is extremely unfair.

2.2. Environmental Impacts of Digitalization

Simon Kuznets (1955) stated that, at the beginning of a country's economic development, environmental damage will increase along with income. However, as a country continues to develop, the importance of environmental protection will increase, and as income increases, environmental damage will decrease after a certain threshold. This inverted "U"-shaped relationship is referred to as the environmental Kuznets curve. It is also possible to examine the environmental Kuznets curve in terms of digitalization. Digitalization represents technological progress, and technological progress is one of the foundations of growth. Lee and Brahmarsene (2014) state that information and communication technologies (ICT) enable the more efficient production of goods and services. However, due to increased efficiency in goods and services, the demand for ICT will also increase, which will increase carbon emissions (CO₂). The interpretation of the environmental Kuznets curve in terms of digitalization indicates that CO₂ will initially increase with the increase in ICT, but will subsequently decrease with the development of production technologies (Haldar and Sethi, 2022).

Higon et al. (2017) explain this situation in four stages. The first stage is a further increase in emissions with economic growth. The second stage is the sophistication of production structures, the transition to higher value-added production, and a decrease in emissions per unit of output. In the third stage, as production inputs become less emission-producing as a result of the second stage, emissions per output decrease even further. Finally, production technologies become more environmentally friendly, leading to the renewal of production processes and a decrease in emissions. In this case, carbon emissions increase in the first stage and begin to decrease in subsequent stages, resulting in an inverted U-shaped relationship.

There are several studies supporting the EKC hypothesis adapted to digitalization. Haldar and Sethi (2022) analyze 16 developing countries between 2000 and 2018. Using quantile regression, the study reveals findings supporting the EKC hypothesis. Li et al. (2021), on the other hand, use a fixed-effects model in their study covering 190 countries for the period 2005-2016, demonstrating that while carbon emissions increased in the short term, there are findings

supporting the EKC hypothesis in the long term. Finally, Higon et al. (2017) used the Driscoll-Kraay and IV-2SLS methods for 142 countries between 1995-2010, and found findings supporting the EKC hypothesis. Additionally, their findings reveal that the threshold level is higher in developing countries and relatively lower in developed countries.

Murugesan (2008) is one of the pioneering studies that focuses directly on the positive environmental impacts of digitalization. He systematically defines the concept of "Green Information Technologies" and addresses several environmental issues of this rapidly growing sector, such as increased energy consumption, carbon emissions, and e-waste. The study focuses on four main application areas: 1. Green Design, 2. Green Production, 3. Green Usage, and 4. Green Waste Management. Through these four focal points, the study emphasizes the role of digital solutions, such as virtualization in data centers, server consolidation, energy-efficient hardware, and energy-efficient software, in reducing their environmental impacts, and emphasizes the proper management of the digitalization process.

Various studies support the green technology approach in the literature. Sun and Wu (2024), using a fixed-effects model for 30 cities in China between 2011 and 2019, demonstrate that digitalization has a reducing effect on carbon emissions, although this varies by region. Similarly, Shang and Niu (2023) highlight the positive environmental impacts of digitalization using the IV-2SLS model, using data from 38 banks in China between 2010 and 2021. Afjal et al. (2023) demonstrate that digitalization has a significant impact on reducing carbon emissions using the FMOLS method, using data from 15 developing countries between 2005 and 2020. Haseeb et al. (2019) analyze BRICS countries using seemingly unrelated regression for the period 1994 to 2014. They obtain findings that digitalization positively impacts environmental quality. Ozcan and Apergis (2018) examine 20 developing countries between 1990 and 2015 and use the Panel AMG method. They obtain findings that demonstrate that digitalization positively impacts carbon emissions. Finally, Al-Mulali et al. (2015) use data from 77 countries between 2000 and 2013 to demonstrate that digitalization increases carbon emissions using the 2SLS method.

Murugesan (2008) emphasized that digitalization will have a positive impact on the environment, but he conditioned this on proper management and organization. Although not directly mentioned, he also touches on the rebound effect, which will be examined in subsequent sections.

The rebound effect essentially argues that increased efficiency will further increase energy consumption. The first theoretical approach to this topic was proposed by Khazzoom (1980), using neoclassical economics. Khazzoom (1980) argues that increased efficiency in automobiles and energy-powered household appliances resulting from technological advances will increase both consumption and production, thereby increasing energy consumption. He emphasizes that previous studies that considered only the energy demand of a single product are unrealistic. Technological progress makes any product more energy-efficient. Therefore, less energy is needed to produce the same amount of product (Lange and Berner, 2022). However, as a product becomes more efficient, its cost per unit of service decreases. Price decreases in this situation lead to increased consumption. This is because individuals tend to consume more productive services, which increases energy demand. This increase in energy demand resulting from energy savings is called the rebound effect (Magee and Devezas, 2017).

Numerous studies supporting the rebound effect stand out in the literature. Yang et al. (2025), using data from 13,551 companies from 61 countries between 2013 and 2021, show that digitalization increases carbon emissions with the help of a fixed effects model. Li and Tang (2024), using data from 30 cities in China between 2013 and 2021, show that developing technologies stemming from data centers and digitalization significantly increase carbon emissions with the help of the PVAR model. Peng et al. (2023), using data from 285 cities in China, presented findings supporting the rebound effect for the period 2007-2019. Pu et al. (2024) draw attention to the negative impacts of digitalization on the environment in BRICS countries with the help of quantile regression in the period 1995-2022. Adha et al. (2023) show that digitalization increased energy demand and led to an increase in carbon emissions in Taiwan using the PMG method during the 2004-2018 period. Batool and Rehman (2022) show that the widespread use of digitalization in industry increased carbon emissions in China using the threshold regression method during the 1990-2021 period. Danish et al. (2018) show that digitalization increased carbon emissions using the MG and AMG methods using data from 11 countries during the 1990-2015 period. Finally, Majeed (2018) presents findings supporting the rebound effect in developing countries using POLS and GMM using data from 132 countries during the 1980-2016 period.

2.3. Environmental Impacts of Banking

A number of approaches have been outlined in the relevant literature regarding the impact of the banking and financial sector on the environment. The most prominent of these is the dirty industry finance approach. Accordingly, the primary objective of banks and financial institutions is to maximize their short-term profits. In line with this priority, they do not hesitate to support projects that have a high potential for environmental pollution but also high profit margins (Destek et al., 2025).

It is possible to come across numerous studies in the literature supporting the dirty industry finance approach. Mehmood (2023), using data from 11 developing countries between 1990 and 2020, shows that banks' loans to the private sector have an increasing effect on carbon emissions with the CS-ARDL method. Radulescu et al. (2022), in their study covering 27 OECD countries over the period 1990-2018, show that development in banking increases the ecological footprint with quantile regression. Ehigiamusoe and Lean (2019), using data from 61 countries between 1990 and 2014, obtained findings that financial development increases carbon emissions in some countries with the PMG method. Jiang and Ma (2019), in their analysis of 128 countries between 2000 and 2014, use the fixed effects model and GMM. Findings show that financial development increases carbon emissions on a global scale. Haseeb et al. (2019) use panel apparently unrelated regression to show that financial development increases carbon emissions in BRICS countries between 1994 and 2014. Finally, Salahuddin et al. (2016) use the ARDL method to show that financial development increases carbon emissions in Australia between 1985 and 2012.

However, the green finance approach suggests that banking positively impacts the environment (Ganda, 2019). According to this approach, banks consider ESG criteria when formulating their credit policies and support environmentally friendly projects. They internalize environmental risks and reflect them in their loans (Khan et al., 2021).

There are several studies supporting the green finance approach in the literature. Halдар et al. (2023) demonstrate that financial development supports environmental sustainability in 16 developing countries between 2000 and 2018 using fixed effects and GMM methods. Jan et al. (2023) analyzed 16 Islamic banks in Malaysia and 12 in Indonesia for the 2009-2018 period and, using the PCSE method, found that banks that made progress in digital finance were better aligned with sustainable development goals. Rafique et al. (2020) found that financial development reduced carbon emissions in BRICS countries between 1990 and 2017 using the Panel AMG method. Omoke et al. (2020) demonstrate that positive shocks to financial development reduced the ecological footprint and carbon emissions in Nigeria between 1971 and 2014 using the NARDL method. Finally, Majeed and Mazhar (2019) argue that all components of financial development improve environmental quality using fixed effects and the Driscoll-Kraay model in 131 countries during the period 1971-2017.

Finally, there are studies in the literature that determine that banking and financial development variables do not have a significant impact on the environment. For example, Ozturk and Acaravci (2013) found that banking had no significant impact on CO₂ in the long run in their analysis of Turkey. Omri et al. (2015) and Charfeddine and Kahia (2019) determined that the impact of financial development on the environment was insignificant in their analysis of MENA countries. Dogan and Turkekul (2016) tested the EKC hypothesis in the US and found that the impact of financial development on the environment was insignificant in some cases. Ghorashi and Alavi (2018), in their study of various sectors in Iran, determined that financial development did not affect carbon emissions. Finally, Gök (2019) noted in his meta-analysis that both positive, negative, and insignificant findings were frequently found in the literature, and that this was due to measurement discrepancies and heterogeneity.

2.4. Environmental Impacts of Natural Resource Depletion

The basis of natural resource depletion is predicated on the difficulty of accessing resources that are impossible to produce, non-renewable, or limited as a result of the increasing scarcity of resources and the resulting change in consumption behaviour (Stevens et al., 2015). Changes in consumption behavior, in turn, increase environmental damage. There is a fairly extensive literature on this subject (Hussain et al., 2020; Huang et al., 2023; He, 2024; Xu et al., 2024; Li et al., 2025), and it is a widely accepted view that natural resource depletion will increase environmental damage. There are also different perspectives on this view. For example, Hotelling (1931) states that as resources diminish, access to the remaining resources will become more difficult and that poorer quality resources will become more costly, drawing attention to the increase in marginal cost. Ahakwa et al. (2023) argue that while this situation can be offset to some extent by technological advancement, it is unsustainable in the long term, and the destruction cannot be prevented. Amer et al. (2024) argue that as resources become depleted, access to remaining resources will become more difficult, forcing further environmental destruction. They cite the destruction of forests, sensitive habitats, and oceans as examples of this. Stevens et al. (2015) argue that governments whose primary source of income depends on natural resources will disregard environmental protection. Similarly, Byaro et al. (2022) argue that societies that rely on natural resources will become more destructive as resources diminish.

2.5. Literature Gap

In the existing literature, there are many studies examining the effects of banking, digitalization, and natural resource degradation on CO₂ emissions. It has been observed that these studies prefer different proxy indicators, especially in measuring banking and digitalization variables. For example, while Sun and Wu (2024) represented digitalization with a digital economy index calculated specifically for China; Adha et al. (2023), Afjal et al. (2023), Ozcan and Apergis (2018), Salahuddin et al. (2016), and Al-Mulali et al. (2015) used the internet usage rate, and Haldar et al. (2023), Hanif et al. (2022), Batool and Rehman (2022), Haseeb et al. (2019), and Majeed (2018) used ICT. Some studies address digitalization through financial technologies (Fintech) indicators; Mertzanis (2023), Udeagha and Muchapondwa (2023), and Xu et al. (2023) adopt this approach. A similar diversity exists in terms of banking variables. Liu et al. (2024) used bank stability, Mehmood (2023) used private sector loans, Jan et al. (2023) used financial performance indicators, and Shang and Niu (2023) used bank size, savings and debt ratios, and income ratio as proxy variables.

In this context, although there is diversity in the measurement of banking and digitalization variables, studies using both variables together are limited. Additionally, among these limited studies, no study has been found that examines both variables by indexing them. In the literature, studies such as Pu et al. (2024), Hanif et al. (2022), Omoke et al. (2020), Majeed (2018), and Higon et al. (2017) have produced a single index value from correlated indicators by applying the PCA method. However, most of these studies consider only a single variable (either banking or digitalization) and do not take into account the heterogeneous structure of CO₂ emissions. For example, Majeed (2018) and Higon et al. (2017), despite using large country samples, analyzed all countries with a single slope coefficient using linear econometric methods. Pu et al. (2024) partially address these shortcomings by examining the impacts of banking, digitalization, and natural resources on CO₂. However, they evaluate natural resources in terms of the economy's dependence on these resources rather than their depletion. Similarly, when creating an index for banking, they used patent numbers rather than digitalization.

This study addresses existing gaps in the literature in four ways and contributes at both the theoretical and methodological levels. First, by applying PCA to the banking and digitalization indicators, data from different indicators were combined into a single, integrated index structure. This approach minimizes potential multicollinearity among variables and increases the reliability of the measurements. Second, a quantile panel regression method was used to account for differences in the distribution of CO₂ emissions across a large dataset covering 94 countries. This method goes beyond traditional models, focusing on average effects and revealing the differentiating aspects of the relationship between variables at low, medium, and high emission levels. Third, in addition to the banking and digitalization variables, the natural resource degradation indicator was also included in the analysis, providing a comprehensive examination of the effects of natural resource depletion on CO₂ emissions. Fourth, no study in the literature addresses the complex structure of banking, digitalization, natural resource depletion, and CO₂ emissions used in this study. This allows us to better understand the environmental impacts of banking, digitalization, and natural resource depletion. Combined, this study utilizes both indexing techniques and distribution-sensitive econometric methods, providing innovative, robust, and policy-applicable results.

In conclusion, the study has two key features that distinguish it from existing literature. Firstly, no study was found that indexed both banking and digitalization variables. Indexing both variables reduces the risk of multicollinearity in the findings, increases their reliability, and allows for more accurate interpretation. Secondly, although some studies have investigated the effects of banking and digitalization on CO₂ using quantile regression methods, none have used the simultaneous quantile regression method. This method estimates different quantiles simultaneously and eliminates the standard error distortions resulting from separate estimations across different quantiles using the bootstrap method, making the estimates much more reliable.

The study aims to explain various hypotheses with equation 2 presented below:

$$CO2_{i,t} = \beta_0 + \beta_1 DIGI_{i,t} + \beta_2 DIGI^2_{i,t} + \beta_3 BANK_{i,t} + \beta_4 NATDEP_{i,t} + \beta_5 ELOGC_{i,t} + \beta_6 ELRENEW_{i,t} + \beta_7 IND_{PW_{i,t}} + \mu_{i,t} \quad (2)$$

H₀: Digitalization has no significant impact on the environment ($\beta_1=0$)

H₁: The impact of digitalization on the environment supports the environmental Kuznets curve, which suggests that environmental damage will first increase with increasing demand and then decrease with technological development ($\beta_1>0, \beta_2<0$)

H₂: The impact of digitalization on the environment supports the rebound effect, which states that increased productivity will increase demand ($\beta_1>0, \beta_2\geq 0$)

H₃: Banking does not have a significant impact on the environment ($\beta_3=0$).

H₄: The environmental impact of banking supports the green finance approach, which argues that environmental damage will be reduced through green banking regulations ($\beta_3<0$).

H₅: The environmental impact of banking supports the dirty industry finance approach, which argues that environmental pollution will increase through credit expansion that ignores the environment ($\beta_3>0$).

H₆: The impact of natural resource depletion on the environment supports the view that environmental destruction will increase as resources decrease ($\beta_4>0$).

If the H₀ hypothesis can be rejected, the H₁ hypothesis supports the environmental Kuznets curve interpretation, while the H₂ hypothesis supports the rebound effect.

3. Econometric Analysis

3.1. Data

Panel data analysis is conducted using data from 2014 to 2021 for 94 countries (countries are listed in Appendix Table A1). Although the selected sample is short in terms of period due to the limited data available on digitalization, it represents the largest number of countries in the specified period. For this purpose, CO₂ per capita is used as the dependent variable, digitalization, banking, and natural resource depletion are used as independent variables, and energy production with fossil fuels, renewable energy production, and industrial production per worker are used as control variables. The variables are explained in Table 1.

Table 1. Variables

Abbreviation	Variables	Sources	References
CO ₂	Air Pollution: Natural logarithm of CO ₂ in metric tons per capita	World Bank	Yang et al. (2024), Pu et al. (2024), Li and Tang (2024), Liu et al. (2024), Sun and Wu (2024), Adha et al. (2023), Afjal et al. (2023), Peng et al. (2023), Xu et al. (2023), Batool and Rehman (2022)
DIGI	Digitalization Index: Created by the author using principal component analysis using data on internet usage rate, mobile cellular subscriptions and broadband usage.	World Bank	Pu et al. (2024), Afjal et al. (2023), Haldar et al. (2023), Hanif et al. (2022), Majeed et al. (2018), Higon et al. (2017), Salahuddin et al. (2016), Al-Mulali et al. (2015)
BANK	Banking Index: It was created by the author using principal component analysis using data on deposit banks' assets, financial system deposits, banks' private loans and liquid liabilities.	World Bank	Pu et al. (2024), Liu et al. (2024), Mehmood (2023), Jan et al. (2023), Shang ve Niu (2023), Omoke et al. (2020)
NATDEP	Natural Resource Depletion: Natural logarithm of natural resource depletion in dollars	World Bank	Li et al. (2025), Xu et al. (2024), He et al. (2024), Huo and Peng (2023), Byaro et al. (2022), Hussain et al. (2020)
ELOGC	Non-Renewable Energy: Natural logarithm of the share of energy produced from Oil, Gas and Coal sources in total electrical energy production.	World Bank	Voumik et al. (2022), Vardar et al. (2022), Rosselot et al. (2021), Wang et al. (2021), Valadkhani et al. (2019)
ELRENEW	Renewable Energy: The natural logarithm of the share of energy produced from renewable energy sources in total electrical energy production.	World Bank	Kongkuah, and Alessa (2025), Justice et al. (2024), Altın (2024), Chen et al. (2022), Voumik et al. (2022), Rosselot et al. (2021), Valadkhani et al. (2019)
IND_PW	Industrial Production: Natural logarithm of industrial production per worker	World Bank	Han et al. (2025), Parveen et al. (2023), Dahal et al. (2023), Avenyo and Tregenna (2022), Hao et al. (2021), Wagner et al. (2020)

3.1.1. Carbon Emissions (CO₂)

The dependent variable of this study is per capita CO₂, which is widely used in the literature to measure environmental pollution. Adha et al. (2023) use CO₂ emissions to measure the environmental impacts of information and communication technologies. Afjal et al. (2023) measure the impact of internet use on CO₂ by substituting digitalization. Xu et al. (2023) investigated the impacts on CO₂ in their study on green finance and fintech; while studies such as Yang et al. (2024) and Pu et al. (2024) used CO₂ emissions as the dependent variable when investigating the environmental impacts of digitalization. Additionally, many studies such as Li and Tang (2024), Liu et al. (2024), Sun and Wu (2024), Peng et al. (2023), and Batool and Rehman (2022) use CO₂ emissions instead of environmental pollution and air pollution.

3.1.2. Digitalization

There are many examples in the literature representing the digitalization variable. For example, studies such as Afjal et al. (2023), Haldar et al. (2023), Salahuddin et al. (2016), and

Al-Mulali et al. (2015) use the internet usage rate as a proxy for digitalization, while Ozcan and Apergis (2018) use internet access as a proxy. In this study, PCA, as applied in studies such as Pu et al. (2024), Hanif et al. (2022), Majeed (2018), and Higon et al. (2017), was applied. For this analysis, Broadband Subscriptions (per 100 people), Mobile Cellular Subscriptions (per 100 people), and Internet Usage Rate data obtained from the World Bank's WDI database for 94 countries and the period 2014-2021 were used. The abbreviation DIGI is used for the variable.

3.1.3. Banking

In the literature, it is observed that more than one variable is used to represent the banking variable, as in digitalization. For example, Liu et al. (2024) used bank stability, while Mehmood (2023) used bank loans to the private sector. Jan et al. (2023) used financial performance, Shang and Niu (2023) used bank size, and Rafique et al. (2020) preferred financial development. This study uses principal component analysis, as applied in studies such as Pu et al. (2024) and Omoke et al. (2020). For this analysis, the data obtained from the World Bank's GFI (Global Financial Inclusion) database for 94 countries and the period 2014-2021, including the ratio of deposit banks' assets to GDP (%), the ratio of financial system deposits to GDP (%), the ratio of deposit banks' private loans to GDP (%), and the ratio of liquid liabilities to GDP (%), were used. The abbreviation BANK is used for the variable.

3.1.4. Natural Resource Depletion

Natural resource depletion is a variable frequently used in the literature to explain carbon emissions. Huo and Peng (2023) investigate the environmental impacts of natural resource depletion, while Xu et al. (2024) and Li et al. (2025) use it to investigate carbon inequality. Byaro et al. (2022) investigate the effects of natural resource degradation and renewable energy on environmental degradation. He et al. (2024) investigate the ecological impacts of natural resource degradation, while Hussain et al. (2020) investigate the effects of natural resource degradation and energy consumption on carbon emissions. The abbreviation NATDEP is used for the variable.

3.1.5. Renewable and Non-Renewable Energy Production

Electricity generated from non-renewable sources is an important factor in the emission of various greenhouse gases. Indeed, it is frequently used in the literature among the explanatory variables of CO₂ emissions. For example, Valadkhani et al. (2019) compared the CO₂ effects of renewable and non-renewable energy production for 60 leading countries in environmental pollution; Voumik et al. (2022) made a similar comparison for the G7 countries. Rosselot et al. (2021) investigate the CO₂ effects of renewable and non-renewable electricity production in the Chinese sample. The findings clearly show that the environmental impacts of renewable sources are much more limited. In addition, Vardar et al. (2022) and Wang et al. (2021) directly investigate the effects of fossil fuels on CO₂ emissions. The findings reveal the devastating effects on the environment. Finally, Kongkuah, and Alessa (2025), Justice et al. (2024), Altın (2024), and Chen et al. (2022) directly investigate the effects of renewable energy production on CO₂ and demonstrate its positive environmental impact. In this study, as in the literature, both

renewable and non-renewable energy production are used as explanatory variables for CO₂ emissions. The abbreviations ELOGC are used for non-renewable energy production and ELRENEW for renewable energy production.

3.1.6. Industrial Production

Industrial production per worker is frequently used in the literature to explain CO₂ emissions. For example, Han et al. (2025) conduct a similar analysis using industrial production per worker, based on the inverted U-shaped relationship between income per capita and CO₂ in the environmental Kuznets curve. Dahal et al. (2023) and Wagner et al. (2020) investigate the effect of the industrial output/worker ratio on the CO₂/worker ratio. Studies such as Parveen et al. (2023), Avenyo and Tregenna (2022), and Hao et al. (2021) focus on the effects of industrial production per capita on CO₂ emissions per capita. The accepted view in the literature is that an increase in industrial production per worker leads to an increase in CO₂ emissions. This study uses the abbreviation IND_PW for industrial production per worker. Table 2 presents the correlation matrix for the variables. A high correlation* between independent variables can lead to a multicollinearity problem (Alin, 2010). However, an examination of Table 2 reveals no high correlation between independent variables that could lead to a multicollinearity problem.

Table 2. Correlation Matrix

	CO ₂	DIGI	BANK	NATDEP	ELOGC	ELRENEW	IND_PW
CO ₂	1						
DIGI	0.9570*** (0.0000)	1					
BANK	-0.4260*** (0.0000)	-0.4134*** (0.0000)	1				
NATDEP	0.2810*** (0.0000)	0.1939*** (0.0000)	-0.0023 (0.9497)	1			
ELOGC	0.1362*** (0.0002)	0.0866** (0.0175)	-0.0391 (0.2840)	0.0766** (0.0357)	1		
ELRENEW	-0.0210 (0.5660)	0.0194 (0.5958)	-0.0524 (0.1510)	0.0839** (0.0214)	-0.3998*** (0.0000)	1	
IND_PW	0.2808*** (0.0000)	0.2659*** (0.0000)	-0.3692*** (0.0000)	0.0491 (0.1782)	-0.1517*** (0.0000)	0.0408 (0.2642)	1

Table 3 presents descriptive statistics for the variables. Examining descriptive statistics is an important step in identifying outlier observations and selecting a method (Wooldridge, 2016). An examination of Table 3 reveals that variables such as the dependent variable CO₂ and the independent variables DIGI, NATDEP, and ELOGC are distributed across a relatively wide range compared to other variables. This is particularly expected for CO₂. Indeed, an examination of the CO₂ distribution in Part 2 of the study revealed not only an unequal distribution but also a gap between the lowest and highest levels.

* There is no definitive threshold in the literature for correlations among independent variables to create multicollinearity. However, when examining primary sources such as Kennedy (2008), Gujarati & Porter (2009), and Wooldridge (2016), a correlation value greater than |0.8| indicates a situation that should raise serious suspicions of multicollinearity.

Table 3. Descriptive Statistics

Variables		Mean	Standard Deviation	Minimum Value	Maximum Value
CO ₂	overall	3.4947	1.9962	-1.2385	9.4507
	between		2.0036	-1.1264	9.3443
	within		0.0873	3.0867	3.7756
DIGI	overall	0.0188	2.7394	-8.0545	8.0576
	between		2.7400	-7.8257	7.6558
	within		0.2580	-1.3932	1.0776
BANK	overall	0.0495	1.1345	-2.8478	3.2460
	between		1.1208	-2.7218	2.3982
	within		0.2063	-0.9184	1.0789
NATDEP	overall	7.9818	2.1754	0.3884	13.8433
	between		2.0742	2.5221	13.1438
	within		0.6859	3.3006	11.3654
ELOGC	overall	3.4179	1.8231	-6.4578	4.6051
	between		1.8094	-6.0542	4.6033
	within		0.2836	-0.2499	6.2272
ELRENEW	overall	3.0540	1.4470	-2.1878	4.7648
	between		1.4247	-1.7158	4.6078
	within		0.2877	1.3166	6.6037
IND_PW	overall	10.0119	1.1242	7.3568	12.9941
	between		1.1267	7.5353	12.6431
	within		0.0787	9.5778	10.3628
Observations	N= 752	n = 8	T = 8		

3.2. Methodology

Especially when we consider dependent variables, Quantile Regression methods that perform different regression estimates by dividing the sample into equal parts are effective methods in cases where a wide range of distribution is observed (Huang and Nguyen, 2018; Clarke et al., 2021). Indeed, when analyzing carbon emissions, many studies, such as Audi et al. (2025), Pu et al. (2024), Boyce and He (2023), Peng et al. (2023), Lou et al. (2023), Xu et al. (2023), and Haldar and Sethi (2022), have used the quantile regression method. This study also uses the Simultaneous Quantile Regression method for the analysis of CO₂ emissions. This method allows for the simultaneous calculation of beta coefficients from different parts of the regression. In addition, to more clearly see the effects of the heterogeneous structure of CO₂ emissions, the simultaneous quantile regression method is supported by IV-2SLS. This allows for the extent to which an analysis performed for the entire data set differs when performed for different levels of the dependent variable. The IV-2SLS method, preferred in the literature by Shang and Niu (2023) and Higon et al. (2017) in the analyses of CO₂ emissions, allows for instrumental variable estimation. Thus, it produces coefficients that are robust to potential endogeneity problems (Xie et al., 2018). Furthermore, in the simultaneous quantile regression method, the analysis is simulated multiple times, and in this way, the means of both the coefficients and standard errors converge to the true parameter and standard error values (Kitahara et al., 2020). For this reason, simultaneous quantile regression estimates are more resistant to situations that may create deviations in the coefficients and standard errors (Audi et al., 2025).

3.2.1. Panel Simultaneous Quantile Regression

Unlike classical quantile regression, the simultaneous quantile method enables parameter estimates for different quantiles to be obtained in a single optimization process, rather than modelling each quantile separately. Thus, the simultaneous approach enables multiple quantiles to be estimated in a single optimization process, ensuring consistency among parameters (Chernozhukov and Hansen, 2008; Bondell et al., 2010). This method reduces the variance of the estimates by increasing the use of common information and strengthens the comparability of the estimated coefficients across different quantiles (Chernozhukov et al., 2010; Machado and Silva, 2019). The following econometric model, proposed by Koenker (2004) is used in this study:

$$Q_{y_{i,t}|x_{i,t}}(\tau) = \alpha_\tau + x'_{i,t}\beta_\tau + \varepsilon_{i,t,\tau} \quad (3)$$

Here, $\tau \in \{0.20, 0.40, 0.60 \text{ ve } 0.80\}$ represents the τ th quantile. $y_{i,t}$, represents the dependent variable vector in the τ condition, while $x'_{i,t}$ represents the independent variable vector in the τ condition. α_τ and β_τ represent the constant term in the τ condition and the coefficient parameters in the τ condition, respectively. $\varepsilon_{i,t,\tau}$ represents the error term here.

Using the Panel SQR method, it is possible to observe how the effects of heterogeneous variables within the sample, such as income groups or emission levels, differ at different levels. This allows policymakers to develop differentiated policies specific to different levels (Khan et al., 2024). Simultaneous quantile panel regression does not require a normal distribution of error terms and is robust to outliers (Koenker, 2004).

3.2.2. IV-2SLS

In panel data analysis, the IV-2SLS model aims to address potential endogeneity issues (Greene, 2018). Unlike traditional regression, an independent variable is estimated as a dependent variable and its residuals are obtained, thus eliminating the effects of the interrelationship between variables (Cameron and Trivedi, 2005). This process can be described by the following equations:

$$\begin{aligned} Y_{i,t} &= \delta_1 X_{i,t} + \delta_2 Z_{1i,t} + u_t \\ X_{i,t} &= \delta_3 Z_{1i,t} + \delta_4 Z_{2i,t} + v_t \end{aligned} \quad (4)$$

With an instrumental variable estimated in this way, potential endogeneity problems can be eliminated (Wooldridge, 2016). In this respect, the IV-2SLS method is preferred in this study as a complementary method to the Panel SQR method.

3.3. Findings

The findings are presented in Table 4[†]. First, we examine the diagnostic tests presented below the table. The tests indicate that the IV-2SLS model suffers from autocorrelation and heteroscedasticity issues. Therefore, the IV-2SLS findings are presented with robust standard errors. Furthermore, the multicollinearity and normality tests provide robust results.

Table 4. Panel SQR and IV-2SLS Findings

	Q20	Q40	Q60	Q80	IV-2SLS
DIGI	0.702 (0.000) ***	0.687 (0.000) ***	0.674 (0.000) ***	0.670 (0.000) ***	0.700 (0.000) ***
DIGI_SQ	0.010 (0.000) ***	0.013 (0.000) ***	0.015 (0.000) ***	0.013 (0.000) ***	0.011 (0.000) ***
BANK	-0.056 (0.038) **	-0.033 (0.223)	-0.012 (0.690)	0.012 (0.542)	-0.052 (0.019) **
NATDEP	0.049 (0.000) ***	0.067 (0.000) ***	0.078 (0.000) ***	0.095 (0.000) ***	0.091 (0.000) ***
ELOGC	0.048 (0.005) ***	0.034 (0.063) *	0.038 (0.021) **	0.059 (0.035) **	0.044 (0.000) ***
ELRENEW	-0.054 (0.001) ***	-0.052 (0.016) **	-0.048 (0.015) **	-0.030 (0.276)	-0.045 (0.004)***
IND_PW	0.023 (0.395)	0.058 (0.040) **	0.113 (0.000) ***	0.147 (0.000) ***	0.085 (0.000) ***
C	2.365 (0.000) ***	2.175 (0.000) ***	1.754 (0.000) ***	1.454 (0.000) ***	1.794 (0.000) ***
Obs		752			658
R-Square	0.757	0.758	0.757	0.758	0.757
Diagnostic Tests					
Modified Wald test for groupwise heteroskedasticity					0.000***
Wooldridge test for autocorrelation					0.000***
VIF (Mean)					4.48
Jarque-Bera normality test					0.775
Skewness and kurtosis tests for normality					0.813

When examining the 20th quantile of carbon emissions, digitalization has a positive and statistically significant impact on carbon emissions. A 10% increase in digitalization increases carbon emissions by approximately 7%. Similarly, the square of digitalization has a positive and statistically significant effect on carbon emissions. A 10% increase in the square of

[†] The findings presented in Table 4 include the coefficients and p-values for the Panel SQR and IV-2SLS analysis methods. The Panel SQR method was estimated at the 20th, 40th, 60th, and 80th quantiles for both models. These estimation methods were performed using Stata 17. Furthermore, when using the Panel SQR method, the bootstrap value was set to 1000 to prevent the possibility of deviation in both the coefficients and the standard errors. Additionally, robust standard errors were used in the IV-2SLS model because the bootstrap feature was not available.

digitalization increases carbon emissions by approximately 0.10%. However, banking has a negative and statistically significant impact on carbon emissions. A 10% improvement in banking reduces carbon emissions by approximately 0.56%. Furthermore, while natural resource depletion and non-renewable energy positively affect carbon emissions, renewable energy negatively affects carbon emissions, and these findings appear statistically significant. Accordingly, a 10% increase in natural resource depletion increases carbon emissions by approximately 0.49%, a 10% increase in non-renewable energy increases carbon emissions by approximately 0.48%, and a 10% increase in renewable energy reduces carbon emissions by approximately 0.54%. Finally, industrial production per worker was found to be statistically insignificant.

When examining the 40th quantile of carbon emissions, digitalization has a positive and statistically significant impact on carbon emissions. A 10% increase in digitalization increases carbon emissions by approximately 6.87%. Similarly, the square of digitalization has a positive and statistically significant effect on carbon emissions. A 10% increase in the square of digitalization increases carbon emissions by approximately 0.13%. However, banking does not have a statistically significant impact on carbon emissions. Furthermore, while natural resource depletion, non-renewable energy, and industrial production per capita increase carbon emissions, renewable energy reduces carbon emissions, and these findings appear statistically significant. Accordingly, a 10% increase in natural resource depletion increases carbon emissions by approximately 0.67%, a 10% increase in non-renewable energy increases carbon emissions by approximately 0.34%, and a 10% increase in industrial production per capita increases carbon emissions by approximately 0.58%, while a 10% increase in renewable energy reduces carbon emissions by approximately 0.52%.

When examining the 60% quantile of carbon emissions, digitalization has a positive and statistically significant impact on carbon emissions. A 10% increase in digitalization increases carbon emissions by approximately 6.74%. Similarly, the square of digitalization has a positive and statistically significant effect on carbon emissions. A 10% increase in the square of digitalization increases carbon emissions by approximately 0.15%. However, banking has no statistically significant impact on carbon emissions. Furthermore, while natural resource depletion, non-renewable energy, and industrial production per capita increase carbon emissions, renewable energy reduces carbon emissions, and these findings appear statistically significant. Accordingly, a 10% increase in natural resource depletion increases carbon emissions by approximately 0.78%, a 10% increase in non-renewable energy increases carbon emissions by approximately 0.38%, and a 10% increase in industrial production per capita increases carbon emissions by approximately 1.13%, while a 10% increase in renewable energy reduces carbon emissions by approximately 0.48%.

When examining the 80% quantile of carbon emissions, digitalization has a positive and statistically significant impact on carbon emissions. A 10% increase in digitalization increases carbon emissions by approximately 6.70%. Similarly, the square of digitalization has a positive and statistically significant effect on carbon emissions. A 10% increase in the square of digitalization increases carbon emissions by approximately 0.13%. However, banking has no statistically significant impact on carbon emissions. Furthermore, while natural resource depletion, non-renewable energy, and industrial production per capita increase carbon emissions, renewable energy banking has no statistically significant impact on carbon emissions. Accordingly, a 10% increase in natural resource degradation increases carbon

emissions by approximately 0.95% and a 10% increase in industrial production per capita increases carbon emissions by approximately 1.47%, while a 10% increase in non-renewable energy increases carbon emissions by approximately 0.59%.

Finally, the findings of the IV-2SLS analysis, which analyzes the entire panel, are presented. According to the findings obtained with this method, a 10% increase in digitalization increases carbon emissions by approximately 7%. Similarly, the square of digitalization has a positive and statistically significant effect on carbon emissions. A 10% increase in the square of digitalization increases carbon emissions by approximately 0.11%. However, a 10% increase in banking reduces carbon emissions by approximately 0.52%. Furthermore, natural resource depletion, non-renewable energy, and industrial production per worker positively affect carbon emissions, while renewable energy negatively affects carbon emissions, and these findings are statistically significant. Accordingly, a 10% increase in natural resource degradation, non-renewable energy, and industrial production per capita increases carbon emissions by approximately 0.91%, 0.44%, and 0.85%, respectively. Finally, a 10% increase in renewable energy reduces carbon emissions by 0.45%.

The findings obtained show that the square of digitalization is positive and statistically significant at all levels. This means that digitalization does not have an inverted U-shaped relationship with carbon emissions. Digitalization triggers carbon emissions. This finding allows us to reject hypotheses H0 and H1 of the model. It demonstrates that digitalization has negative environmental impacts across the analyzed sample, and fails to reject hypothesis H2, providing evidence supporting the rebound effect.

4. Conclusion and Discussion

In this study, the effects of banking, digitalization, and natural resource depletion on CO₂ emissions were analyzed using SQR and IV-2SLS methods for 94 countries and the period 2014-2021. The findings show that digitalization has positive effects on CO₂ and support the findings of studies providing findings supporting the rebound effect (Danish et al., 2018; Majeed, 2018; Freitag et al., 2021; Li et al., 2021; Batol and Rehman, 2022; Adha et al., 2023; Peng et al., 2023; Li and Tang, 2024; Pu et al., 2024; Yang et al., 2025). However, the impact of banking on CO₂ is heterogeneous. While the findings of Q20 and IV-2SLS support the green finance approach stating that the impact of banking on the environment is positive (Danish et al., 2018; Ozcan and Apergis, 2018; Majeed and Mazhar, 2019; Omoke et al., 2020; Rafique et al., 2020; Hanif et al., 2022; Halder et al., 2023; Jan et al., 2023; Lin et al., 2024), the findings of other quantiles support the findings of studies indicating that banking does not have a statistically significant impact on the environment (Ozturk and Acaravci, 2013; Omri et al., 2015; Dogan and Turkekul, 2016; Ghorashi and Alavi, 2018; Charfeddine and Kahia, 2019). Finally, natural resource depletion increases CO₂ emissions. These findings support numerous studies in the literature indicating that natural resource depletion increases environmental destruction (Hotelling, 1931; Stevens et al., 2015; Hussain et al., 2020; Byaro et al., 2022; Ahakwa et al., 2023; Huang et al., 2023; Amer et al., 2024; He, 2024; Xu et al., 2024; Li et al., 2025).

The findings confirm the rebound effect across all quantiles. The negative impact of digitalization on air pollution suggests that the energy demand created by developing

technology and increased efficiency is offset by increased energy production and air pollution. The reduced energy demand in consumption is reversed by increased consumption. Furthermore, while the acceleration of digitalization by recently developed artificial intelligence technologies appears to be a positive development, the high energy demand required by AI technologies overshadows this positive development. However, the negative impact of digitalization appears to diminish as we move to higher quantiles. However, these differences are not significant. The fact that countries in higher quantiles are more industrially developed and have higher incomes may indicate more complex relationships underlying high carbon emissions. This could be addressed in future studies.

When examined from a banking perspective, different findings emerge across different quantiles. While findings supporting the green finance approach were obtained in Q20, no significant relationship emerged in other quantiles. A possible explanation for this is that the countries with the lowest carbon emissions, at the Q20 level, are less industrialized and have weaker banking systems. However, countries with higher carbon emissions are largely comprised of developing and developed countries with more established banking systems. Considering developing countries in particular, while green finance approaches are developing due to environmental pressures, it is likely that growth pressures will also support non-environmental projects. Consequently, the mutual neutrality of green finance and dirty industry financing forces the banking sector to become neutral regarding air pollution.

Finally, natural resource depletion, as expected, increases air pollution. In particular, its increasing impact at higher quantiles suggests that as resources become depleted in more industrialized countries, the search for more resources further fuels environmental degradation. This poses a significant problem, especially for countries dependent on natural resources.

Following the discussion of the findings, some critical policy recommendations are presented. First, the findings of this study reveal the positive environmental impacts of renewable energy. In light of these findings, it is recommended that renewable energy use be mandatory in facilities that utilize various energy-intensive digital technologies (data centers, blockchain mining, 5G data centers, etc.). While mandating the use of renewable energy sources in the licensing of such facilities does not affect CO₂ emissions from consumption sources, it will positively contribute to the environment by reducing CO₂ emissions from production. Similarly, environmental sustainability can be achieved by monitoring every stage of production and consumption. A prime example of this is the EcoDesign Directive implemented in EU countries. The EcoDesign Directive is a policy tool that EU countries use to ensure environmental sustainability, starting from the design phase of manufactured products and extending throughout their entire life cycle (Mathieux et al., 2020). Similarly, determining the energy consumption of products from the very beginning of production and comparing it with the minimum energy consumption calculated for each stage, and issuing special certificates can reduce energy consumption in production, thereby achieving energy efficiency. Thus, additional taxes can be imposed on products that consume more energy than expected during production steps, enabling a target for energy efficiency in the production phase. A significant contribution of this is to reduce environmental impacts by penalizing companies that use excessive amounts of energy to produce products that could have been produced with less energy and rewarding companies with optimal energy consumption.

Findings have shown that banking has varying impacts on different levels of CO₂ emissions, yet it is largely ineffective on the environment. In light of this, several recommendations are offered to positively impact the environmental impact of banking. First, the banking sector should internalize environmental risks. Banks, particularly when granting loans, could request reports on environmental risks from businesses. It could be made mandatory for them to identify and propose projects to prevent or mitigate relevant environmental risks. Similarly, in funding the private sector, priority could be given to businesses committed to renewable energy production and/or consumption. This could encourage the use of renewable energy, contributing to the reduction of CO₂ emissions. A second recommendation is to mainstream the polluter-pays principle. Based on this principle, if loans provided by banking and financial institutions increase environmental damage, the lender, along with the business, could be held financially responsible for this damage. This policy, in support of the first policy recommendation, would encourage banks and financial institutions to be more selective in granting loans and to monitor their use more closely. Thus, the institution, knowing that it will incur a financial burden due to environmental degradation after granting the loan, will not want to take this financial risk.

Finally, several policy recommendations are offered to mitigate the effects of natural resource depletion on CO₂ emissions. First, as evidenced by the findings of this study, the need to restrict non-renewable energy production, which has negative environmental impacts, is crucial. Their production and consumption, particularly coal and oil exploration, cause significant environmental pollution. Companies conducting exploration can be required to implement afforestation efforts commensurate with the damage caused by these activities, in addition to deterrent fines. This would force companies to make efforts to minimize the environmental damage they cause. However, the need for these fossil fuels should not be overlooked. One important policy option would be to mandate the use of renewable energy throughout the exploration, extraction, and production phases of fossil fuels. This would reduce the environmental damage caused by fossil fuels to some extent. Similarly, companies engaged in the exploration of various minerals could be incentivized through tax breaks and government support to transition to renewable energy use during the exploration, extraction, and production of these minerals. The proposal to internalize environmental risks related to banking could play a complementary role in this regard. Requiring financial institutions that provide loans for the exploration, extraction, and production of fossil fuels and various minerals to use renewable energy for these activities could reduce the environmental impacts of both banking and natural resource depletion.

There are some limitations in this study due to the time dimension. First, the fact that digitalization is a newly widespread issue of the 21st century results in limited retrospective data availability. Therefore, a short period of time (2014-2021) precludes a long-term analysis. Second, incomplete data from more recent years necessitated limiting the period to 2021. Third, due to significant gaps in the data on energy consumption, the analysis could only be examined from the perspective of energy production. As a result, the policy recommendations presented are focused on energy production to avoid overstating the findings. Finally, to avoid exceeding the quantitative page limits for articles, the empirical analysis could not be further elaborated from various perspectives.

This study uses quantile regression to analyze carbon emission quintiles. Future studies could examine the relationship between carbon emissions and income levels by constructing

separate models for low-, lower-middle-, middle-, upper-middle-, and high-income countries. Furthermore, the study could be expanded to include a spatial dimension by considering neighboring countries and examining whether they trigger carbon emissions using spatial panel data methods. Figure 1 reveals that carbon emissions are concentrated in Asian countries. Future studies could explore the possible causes of this situation and potential solutions. Similarly, a larger sample could be used to analyze the carbon GINI index and reveal the carbon distribution, examining the similarities between countries in higher groups in terms of regional, economic, political and sociological characteristics.

Declaration of Research and Publication Ethics

The data used in the study are publicly available and do not require ethics committee approval.

Researcher's Contribution Rate Statement

First author's contribution: Authorship of the main chapters, data collection, econometric analysis, preparation of the literature, development of the study idea, preparation of the bibliography and layout.
Second author's contribution: Consulting on the study, language checking, and editing.

Declaration of Researcher's Conflict of Interest

There are no potential conflicts of interest in this study.

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APPENDIX

Table A1. Country List

Albania	Croatia	Ireland	Mozambique	Seychelles
Algeria	Czechia	Israel	Namibia	Slovak Republic
Angola	Denmark	Italy	Netherlands	Slovenia
Armenia	Djibouti	Japan	New Zealand	South Africa
Australia	Dominican Republic	Kazakhstan	Nicaragua	Spain
Austria	Ecuador	Kenya	North Macedonia	Sweden
Azerbaijan	Egypt, Arab Rep.	Korea, Rep.	Norway	Thailand
Bangladesh	El Salvador	Kyrgyz Republic	Pakistan	Togo
Belarus	Estonia	Latvia	Panama	Tunisia
Belgium	Finland	Lesotho	Paraguay	Türkiye
Benin	France	Lithuania	Peru	Uzbekistan
Bosnia and Herzegovina	Georgia	Luxembourg	Philippines	Viet Nam
Botswana	Germany	Madagascar	Poland	Zambia
Brazil	Ghana	Malaysia	Portugal	Zimbabwe
Bulgaria	Greece	Maldives	Qatar	
Cabo Verde	Guinea-Bissau	Mauritius	Romania	
Chile	Honduras	Mexico	Russian Federation	
China	Hungary	Moldova	Rwanda	
Colombia	Iceland	Mongolia	Samoa	
Costa Rica	Indonesia	Morocco	Senegal	

THE CONNECTEDNESS AMONG GREEN BONDS AND OTHER ASSET CLASSES: EVIDENCE FROM EMERGING MARKETS

Yeřil Tahvillerin Dięer Yatırım Araçları ile İliřkisinin İncelenmesi: Geliřmekte Olan Piyasalar Örneęi

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Abstract

Keywords:
Green Bonds,
Emerging Markets,
Financial
Contagion,
Portfolio
Diversification,
Cross-
Quantilogram,
Sustainable
Finance.

JEL Codes:
Q56, G12, F65,
O16, G01, F30.

As climate change intensifies, current climate finance remains insufficient to achieve Paris Agreement goals, particularly in developing countries. Closing this gap requires greater international private capital involvement. However, uncertainties about climate finance instruments in developing markets challenge private investment. This study examines green bonds issued in emerging markets, analyzing their dependencies with debt, equity, and commodity markets using the cross-quantilogram method. Results reveal short-term positive dependencies between green bonds and equity and debt markets, indicating high cross-market contagion initially. Yet, these dependencies diverge after a week. While green bonds maintain a positive medium-term relationship with other debt instruments, their medium-term dependence on equity and commodities turns negative. This negative relationship strengthens under normal market conditions but weakens during extreme market events. These findings highlight green bonds' potential as diversification tools for equity and commodity investors in emerging markets. However, short-term contagion remains a challenge for regulators, demanding further analysis of financial stability implications.

Öz

**Anahtar
Kelimeler:**
Yeřil Tahviller,
Geliřmekte Olan
Piyasalar,
Finansal Bulařma,
Portföy
Çeřitlendirme,
Çapraz
Kantilogram,
Sürdürülebilir
Finans.

JEL Kodları:
Q56, G12, F65,
O16, G01, F30.

İklim deęiřiklięi etkileri řiddetlenirken mevcut finansman akıřı, özellikle geliřmekte olan ölkelerde Paris Anlařması hedeflerini karřılamaya yetersiz kalmaktadır. Bu açığın kapatılması için uluslararası özel sermayenin katılımı şarttır. Ancak geliřmekte olan ölkelerdeki iklim finansmanı araçlarına dair belirsizlikler, özel sermayenin katılımını zorlařtırmaktadır. Bu çalıřma, geliřmekte olan piyasalarda ihraç edilen yeřil tahvillerin, dięer borçlanma araçları, pay ve emtia piyasalarıyla baęımlılıęını Çapraz-Kantilogram yöntemiyle incelemektedir. Sonuçlara göre, kısa vadede yeřil tahvillerin pay ve borçlanma araçlarıyla pozitif baęımlılıęı bulunmakta ve piyasa bulařıcılıęı yüksektir. Ancak baęımlılık zamanla ayrıřmaktadır; yeřil tahvillerin orta vadede dięer borçlanma araçlarıyla pozitif baęımlılıęı sürerken, pay ve emtia piyasalarıyla iliřkisi negatif yönde geliřmektedir. Ayrıca, olaęan piyasa kořullarında bu negatif baęımlılık güçlenirken, aşırı kořullarda zayıflamaktadır. Bulgular, geliřmekte olan piyasalar yeřil tahvilin portföy çeřitlendirmesi için potansiyelini ortaya koymaktadır. Kısa vadede gözlenen bulařıcılık finansal istikrar açısından önem taşımakta ve regülatörlerin bu konuda dikkatli olması, risk aktarım mekanizmalarının ve risk-getiri performanslarının daha ayrıntılı incelenmesi gerekmektedir.

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1. Introduction

The impact caused by climate change has become a reality that will affect not only the future but also the present. In the second decade of the 21st century, the global surface temperature has risen by approximately 1.1 degrees Celsius compared to the pre-industrial era. This temperature rise has led to the retreat of glaciers in the North and South Poles and an increase in the temperature of the oceans and marine waters. Further, there is an increasing trend in the occurrence of natural disasters, including extreme rainfall, hurricanes, heat waves, and droughts (IPCC, 2021). These effects have already begun to have widespread negative consequences, affecting both ecosystems and individuals. Economic losses attributed to climate change have been identified in sectors particularly affected by climatic conditions, including agriculture, forestry, fisheries, energy, and tourism. The negative impacts of climate change can reduce the availability of financial resources owing to losses and damages, thus hindering a country's economic growth. This is particularly the case for developing and least developed countries, which can face further limitations in accessing investment capital (IPCC, 2023). While developed countries have the largest cumulative share of greenhouse gas emissions, emissions in these countries have tended to decline owing to technological investments, productivity increases, and many other reasons. However, greenhouse gas emissions are expected to continue to grow in countries at the beginning of industrialization. As the least developed and developing countries face various difficulties in attracting development capital, the need for new resources has been added to their efforts to combat climate change so that they can access low-emission production technologies and increase their resilience to the harmful effects of climate change. According to the United Nations Framework Convention on Climate Change (UNFCCC, 1992), it is critical to provide additional resources to combat climate change without reducing development investments.

Hence, developed countries, which have the largest share in the release of greenhouse gases accumulated in the atmosphere, started to support the efforts of developing countries to combat climate change with public resources in the 1990s. The resources provided for this purpose are referred to as climate finance. Through the Green Climate Fund (GCF), established in 2010, developed countries that are parties to the UNFCCC committed to mobilizing public-source climate finance. Thereafter, at the Conference of the Parties to the UNFCCC in Paris in 2015, it was agreed to concretize the goals of combating climate change and reduce global emissions in a way that the climate temperature increase by the end of the 21st century does not exceed 2 degrees Celsius; the climate temperature increase is limited to 1.5 degrees Celsius compared to the pre-industrial average; and the necessity of mobilizing the necessary financial resources to achieve these goals is emphasized. However, in practice, the climate finance provided remains far from the amount of investment needed to realize these targets, particularly in developing countries (Buchner et al., 2021). For instance, when the GCF was established in 2010, developed countries committed to gradually increasing their annual climate finance flows to developing countries to reach USD 100 billion by 2020. However, that year, the GCF could only provide USD 55 billion in climate finance (Amighini et al., 2022)

The gap between the targeted climate finance and climate finance provided in practice shows that the targets set out in the Paris Agreement cannot be achieved with public resources alone, although they play a critical role in reducing risk and encouraging private sector engagement. Existing literature (Amerasinghe et al., 2017; Amighini et al., 2022) emphasizes the significance of public investment in climate-related endeavors to incentivize private sector

involvement by fostering market development, facilitating innovation, and managing risks. Nevertheless, attaining the targets established in the Paris Agreement hinges on the active participation of private investment. The engagement of private capital, however—and unlike the public sector, which considers the Public Good—is contingent upon tangible performance indicators, such as risk and return, as well as the predictability of these metrics. Bansal et al. (2016) argue that the impacts of climate change on individuals and the overall economy also affect the risks and returns of firms. Giglio et al. (2021) conclude that physical and transitional risks are the leading economic risks related to climate change and advocate that the unignorable dimensions of these risks have made it imperative to investigate and assess these risks for all financial assets.

The finance literature has mainly addressed these risks in two ways. First, it incorporates these risks into firm and asset valuation models by examining their implications on fundamental financial metrics, such as cash flows, debt coverage, and profitability (Giglio et al., 2018; Huynh and Xia, 2020). The second approach, however, focuses on the correlation and interdependence between assets within the framework of portfolio theory and investment portfolio diversification. This approach revolves around portfolio reallocation necessitated by climate change, which will demand adjustments to conventional assets and the exploration of alternative, environmentally sustainable financial instruments aligned with the objectives of the Paris Agreement. This shift in the global economy has led researchers and investors to evaluate new investment alternatives and reallocate their portfolios. Krueger et al. (2019) report that institutional portfolio investors believe that climate risks, particularly those related to regulation, have consequences for portfolio investments. Most investors surveyed by the researchers indicated that these consequences are not only in the future but are already being felt. Many portfolio managers have reported that they are gradually reducing their fossil fuel investments while increasing the share of sustainable investments in their portfolios. Benedetti et al. (2019) argue that portfolio risk can be reduced by diversifying portfolios in line with policies to reduce carbon emissions.

Buchner et al. (2021) demonstrate that more than half of the investments aligned with carbon mitigation policies are directed toward energy projects, with the majority being provided by debt instruments, particularly green bonds (GBs). According to Glomsrød and Wei (2018), GBs can help address income inequality by increasing the supply of clean energy and the share of labor in the economy and promoting economic growth, as measured by gross domestic product. The rapid development and growth of the green, social, and sustainability (GSS) bond market reflects the manifestation of these developments in climate change policy. First issued in the mid-2000s, these instruments grew from a niche and limited market to a multi-trillion (USD) market in a relatively short time, driven by investor demand. According to the Climate Bond Initiative (CBI) report, the cumulative issuance amount as of June 2023 was approximately USD 4.2 trillion (Harrison et al., 2023). However, concerning emerging markets (EMs), although the issuance of GSS and socially responsible investment instruments in developing countries has shown an accelerated increase, their share in cumulative issuances has not exceeded 20% (IFC and Amundi, 2023). Ferrer et al. (2021) argue that GBs with investment-grade credit ratings do not constitute a separate asset class, exhibiting the volatility of treasury and corporate bonds with higher credit ratings. However, Reboredo (2018) and Nguyen et al. (2021) show that GBs can be useful in hedging equity and commodity assets.

However, almost all research on GBs is based on global GB indices, which cover GBs issued in developed and developing countries. The small share of GBs issued in developed countries means that these indices do not resemble GBs issued in these countries. The literature on GBs fails to answer questions about GBs in developing countries using GB indices, most of which include GBs issued in developed countries. Addressing this gap, our study contributes to the literature in four ways. First, we investigate the bidirectional dependence between global and EMs and GBs; thus, we bind EM GBs to the abundant literature on global GBs. Second, we analyze the dependence of GBs issued in EMs on the debt and equity markets. Third, we test the unidirectional dependence of EM GBs on gold, commodity, and energy markets. Finally, we reapply these tests by controlling for market conditions, enabling us to examine the impact of extreme market conditions on the investigated relationships.

2. Literature Review

The concept of climate finance is defined as "the financial resources mobilized and provided to finance actions that mitigate the effects of climate change and adapt to them, including public climate finance commitments by developed countries under UNFCCC." In this context, the concept points to a vast financial universe ranging from consumer loans, such as those for electric cars and green mortgages, to corporate projects worth billions of dollars. The most prevalent climate finance instrument in capital markets is the "green bond." A bond is defined as "a debt instrument whereby an investor lends funds to an organization for a specific period (longer than one year) at a variable or fixed interest rate". A green bond, in turn, is defined as "any type of bond instrument framed by the Green Bond Principles (GBP)" (International Capital Markets Association, 2021), and the proceeds, or an equivalent amount, are to be used to finance or refinance new and/or existing eligible green projects (Buchner et al., 2021).

A review of the extant literature on green bonds reveals that research in this field is primarily concentrated on two main axes. One axis addresses the "intrinsic value" of green bonds and the risks they carry in this context (Buchner et al., 2021; Cuculiza et al., 2021; Giglio et al., 2021; Sautner et al., 2023). The other axis focuses on the interrelationship and movement of green bonds with other asset classes from the perspective of portfolio diversification (Baur and Lucey, 2010; Reboredo, 2018; Ferrer et al., 2021; Liu et al., 2021; Nguyen et al., 2021; Pham, 2021; Chatziantoniou et al., 2022).

The repercussions of climate change are poised to exert a deleterious influence on the future activities of specific sectors and the overall economy (Martinez-Diaz and Keenan, 2020). These impacts have already resulted in economic damage in many regions, and the severity of this damage is not evenly distributed across regions (IPCC, 2023). Accordingly, the extant literature reveals that climate change affects green bonds through two main channels: physical risks (e.g., heat waves, floods, and droughts disrupting production, thereby increasing default probabilities and risk premiums) and transition risks (e.g., regulation, carbon pricing, and technology shocks creating uncertainty in cash flows and discount rates) (Giglio et al., 2021: 24). Physical climate risk is defined as "risks related to the direct disruption of productive assets as a result of climate change." The presence of physical risk is indicated by adverse effects such as heat waves, drought, and extreme rainfall, which have the potential to impact the operations of companies and the health of individuals. Transitional risk is defined as the set of uncertainties

related to cash flows that arise from the transition to a low-carbon economy. It refers to the risks associated with the changes required in consumption and production as part of the process of combating and adapting to climate change. For instance, increased regulation and oversight of coal-fired power plants can result in reduced profitability or even phased closures (Sautner et al., 2023).

In light of these definitions, it is imperative to underscore the fact that the ramifications of these risks at the company and sector levels are non-uniform and exert an influence on green bond pricing through disparate channels. While transition risk persists as a significant threat, inducing cost pressures and cash flow imbalances for certain companies and sectors, it concomitantly engenders competitive advantages and heightened investment attractiveness for entities that demonstrate high carbon efficiency or a propensity for expeditious green technology adoption. Conversely, physical risks encompass a broader spectrum and are more general in nature. However, the severity of these risks exhibits significant variations depending on spatial and sectoral exposure. In fact, Cuculiza et al. (2021) demonstrate that in regions encountering heat waves, the discrepancy between companies' forecasts and actual earnings escalates considerably in the periods following heat wave events. Consequently, while physical risks generate a general impact, their consequences are more pronounced in companies that are directly exposed to these risks. This asymmetric pattern necessitates the systematic investigation and pricing of climate-related economic and financial risks for all asset classes. It also renders the accurate determination of the cost and attractiveness of climate finance, which plays a pivotal role in mitigating these risks, more critical than ever.

A substantial body of research has examined the role of Green Bonds (GBs) in portfolio diversification rather than their intrinsic value. In this context, the relationship between GBs and total and sectoral equities, commodities, and different bond types, primarily traditional bonds, has been analyzed (Reboredo, 2018; Liu et al., 2021; Nguyen et al., 2021; Pham, 2021; Chatziantoniou et al., 2022). This relationship is predicated on the assumption that the "value" of an asset within a portfolio is contingent not only on its intrinsic characteristics but also on its co-movement with other asset classes in the portfolio (Ferrer et al., 2021). According to the principles of Modern Portfolio Theory (MPT), the contribution of an asset to a given portfolio is contingent not only on its intrinsic risk-return profile, but also on its correlation with other assets (Markowitz, 1952).

As Glomsrød and Wei (2018) have noted, green bonds have the potential to offer macroeconomic benefits such as supporting economic growth and reducing income inequality, in addition to environmental goals like increasing clean energy supply. A substantial body of literature has emerged in the aftermath of the initial issuance, examining this novel financial instrument. While certain studies have concentrated on formulating performance indicators and valuation techniques tailored to these bonds, researchers such as Ferrer et al. (2021) have contended that green bonds do not constitute a distinct asset class, but rather mirror the activities of traditional corporate and treasury bonds. However, a substantial body of research has examined the value of these instruments in the context of portfolio diversification and their relationship with other asset classes, rather than their intrinsic value.

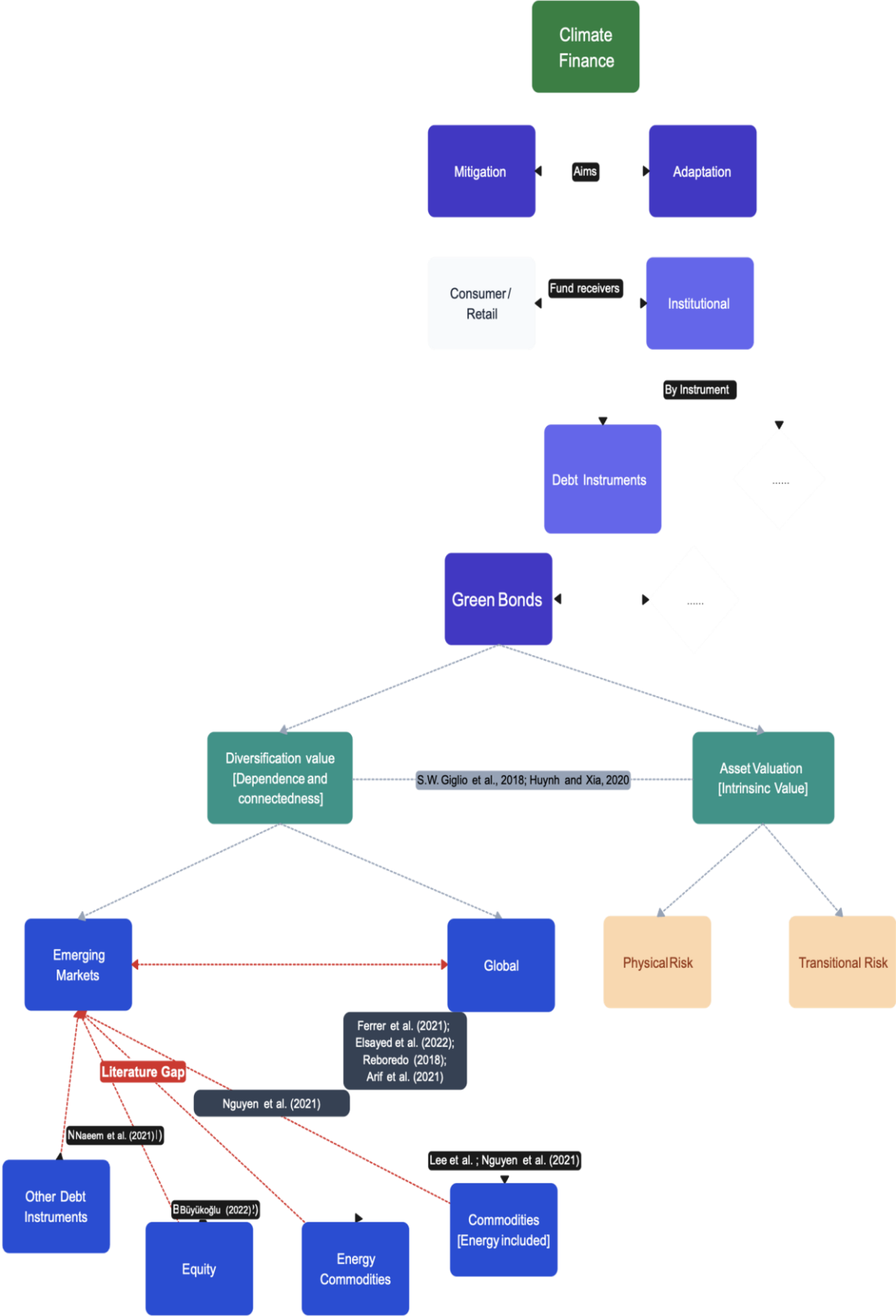


Figure 1. Summary of Empirical Climate Finance Literature

These studies employ global indices, notably the S&P GB and the Barclays Bloomberg GB, to assess the performance of green bonds. However, this approach is not without significant limitations. According to a report by Amundi and IFC (2021), only a small portion of the total green bonds issued in 2021 were in developing countries. This prompts further inquiry into the extent to which global indices can adequately represent the performance of green bonds in these countries. The failure of global indices to adequately reflect the circumstances in developing countries engenders considerable uncertainty for investors and policymakers in these regions. This uncertainty has the effect of increasing the perceived risk of green bonds, which makes it difficult for these countries to meet their climate finance needs.

Consequently, the present study endeavors to address this lacuna in the extant literature, as demonstrated in Figure 1. By selecting an indicator that can more accurately reflect the performance of green bonds in developing countries, the risk-return profile of these assets and their relationship with other investment instruments will be examined in detail. The objective of this study is to provide a more nuanced understanding of the prospects and obstacles associated with green bonds in developing economies.

3. Materials and Methods

3.1. Data and Constraints

This study analyzes the dependence of EM GBs on other asset classes. The study uses nine variables, including EM aggregate debt, global GBs, global-aggregate debt, EM and Developed Markets (DMs) equity instruments, gold, commodities, and energy commodities. Additionally, to control for financial conditions, we use the commonly accepted CBOE Volatility Index (VIX) in addition to the Financial Stress Index (FSI) as proxies for market conditions. The FSI, a relatively new index, has been gaining popularity in recent years. It is being utilized in several studies, such as Elsayed et al. (2022), Lundgren et al. (2018), and comprises 33 financial indicators, including credit conditions, funding, and equity valuation criteria. It is used in both developed and developing countries (Office of Financial Research, n.d.).

Table 1 summarizes our datasets, which consist of 11 variables covering daily prices from January 2, 2015, to March 21, 2022. We converted the price datasets extracted from the Bloomberg data terminal into natural logarithms by taking the price difference between day t and day $t - 1$ and applying the following formula:

$$\ln(P_t) - \ln(P_{t-1}) = \ln(P_t / P_{t-1}) \quad (1)$$

Following Reboredo (2018) and Naeem et al. (2021), we use the Bloomberg MSCI Green Bond and Bloomberg Global Aggregate Total Return indices to represent global GBs and global-aggregate debt, respectively. We use the MSCI World and S&P GSCI Energy Total Return indices, which are popular in the relevant literature, as proxies for DM equity and energy commodity markets. To provide an overview of the commodity market, we use the S&P GSCI Total Return index, which is widely used in the literature (Nguyen et al., 2021; Karim et al., 2022).

Table 1. Datasets Used in This Study

Bloomberg ticker	Index	Proxy for*	Variable*	Price	Obtained obs.	Paired obs.**
JPEIGBCW	J.P. Morgan Green Bond Emerging Markets 10% Capped Index	EM Green Bond	EM GB	Mid	1805	1804
EMUSTRUU	Bloomberg EM USD Aggregate Total Return Index Value Unhedged	EM (Aggregate) Debt	EM DEBT	Close	1882	1804
I31572	Bloomberg MSCI Global Green Bond Index	Global Green Bond	GLB GB	Close	1882	1804
MXWO	MSCI World Index	DM Equity	DM EQU	Close	1882	1804
EMT	Bloomberg Emerging Markets Large & Mid Cap Total Return Index	EM equity	EM EQU	Close	1882	1804
XAU	Gold Spot USD	Gold	GLD	Close	1882	1804
SPGSCITR	S&P GSCI Total Return CME Index	Commodity	COMMD	Close	1882	1804
SPGSENTR	S&P GSCI Energy Total Return Index	Energy Commodity	ENRGY	Close	1882	1804
LEGATRUU	Bloomberg Global-Aggregate Total Return Index Value Unhedged USD	Global (Aggregate) Debt	AGG. DEBT	Close	1882	1804
VIX	CBOE Volatility Index	Volatility	VIX	Close	1882	1804
RFSITOTL	Financial Stress Index Total Global	Financial conditions	FSI	Close	1882	1804

Note: * Used interchangeably throughout the study. ** Paired and price differences naturally logarithmized.

Before moving on to EM GBs, it is necessary to identify a benchmark index for EM equity and EM debt markets. The Bloomberg EM Large and Mid-Cap index is used for the former, while the Bloomberg EM USD Aggregate Total Return Index Value Unhedged is used for EM aggregate debt in the analysis. While this index has the advantage of limiting the impact of exchange rate fluctuations by covering only USD-denominated bonds, it is limited because it does not include debt denominated in other currencies. Additionally, the analysis of these two is constrained by the fact that the selected indices have not previously been used in the literature reviewed.

Finally, a proxy for our dependent variable, EM GBs, must be found. In May 2023, at the time of data collection, two indices existed as flagships representing EM GBs. The first index is the Bloomberg EM GB index, which was not selected owing to its monthly pricing since it was first launched in 2017 up to the last quarter of 2021. From then to May 2023, 408 daily observations were recorded. However, this was not sufficient to produce a significant result using the method used in this study.

The second option was J.P. Morgan GB EMs’ 10% Capped Index. The index data, which were launched in 2014, consist of bond prices issued in EMs and recognized as GBs by the CBI. The index covers EM sovereign and corporate GBs issued in US dollar, euro, and British pound currencies, as well as government bonds issued in the national currencies of 20 EMs, based on specific criteria (Global Index Research, 2022). With daily frequency price data spanning over seven years, this index, while not a perfect indicator, currently appears to be the most

appropriate choice as a proxy for EM GB. However, as outlined in Table 2, it is important to identify and address any limitations that may affect the study results. Nonetheless, as the EM GB market continues to mature, and its indices proliferate and improve, this limitation may gradually disappear.

Table 2. Research Limitations Related to the Dependent Variable

i.	Price movement stagnated between 2015 and 2016, likely owing to limited market size and trading volume.
ii.	The updates to the index were suspended owing to the Russian invasion of Ukraine. The daily price data available from the data provider are limited to the period starting from late 2014 until March 21, 2022.
iii.	Assets in the EM GB index are priced based on daily mid-prices rather than closing prices, unlike other variables in this study, as they use the generally accepted close-to-close price difference approach.
iv.	Although the index price is denominated in US dollars, as with other variables, the assets in the index are denominated in various currencies, and the hedging status of the exchange rates varies. Therefore, the impact of exchange rate movements on the Index price is unknown.
v.	The J.P. Morgan EM GB Index is missing 77 daily observations for the period between January 2, 2015 and March 21, 2022. These observations were not provided by the index or data provider and were spread over several months. To minimize the impact of this omission on the results of this study, we removed all missing observations from the time series of other variables.*

Note: *The dates of observation breaks are shown in the Appendix (see Appendix 1).

As stated in Table 2, the primary time series for the dependent variable, the J.P. Morgan EM GB Index, contained 77 missing daily observations over the seven-year study period. However, this limitation is expected to have a minimal impact on the study's findings for several key reasons. Firstly, these gaps constitute a minimal proportion (less than 5%) of the total 1804 observations and are not accumulated within a single timeframe, but rather, they are distributed sporadically throughout the entire sample period. In order to maintain analytical integrity, the corresponding dates were removed from all other time series, ensuring a perfectly paired dataset. In conclusion, the utilization of log-differenced prices in the calculation of returns inherently accounts for price movements across a missing day. This is due to the subsequent observation capturing the cumulative change. Consequently, due to their sparse distribution and the methodological handling, these missing values do not systematically bias the results.

3.2. Descriptive Statistics

Table 3 presents the descriptive statistics. Gold and developed equity markets have the highest average returns of 0.03%. The EM GB also has a positive average return of around 0.01%, which is comparable to the average return on traditional US dollar-denominated debt instruments of EMs, represented by EM debt Instruments. By contrast, EM GB exhibited lower volatility, with a standard deviation of 0.20%.

The commodity and energy markets have relatively low average returns but high volatility (standard deviation). Nevertheless, the highest standard deviation was observed for the indicators of market conditions. Financial stress ranks first, with a standard deviation of 33%, while the volatility index (VIX) ranks second, with a standard deviation of approximately 8%, indicating that the period covered by this study was highly volatile and exhibited extreme

market behavior. These findings are consistent with the fact that this study covers the COVID-19 and global monetary tightening periods.

Table 3. Descriptive Statistics

Variable	Mean (%)	Min. (%)	Max. (%)	SD (%)	Skewness ¹	Kurtosis ²	Jarque-Bera*	ADF* (12)**	PP* (8)**
EM GB	0.012	-2.80	1.65	0.196	-2.99	46.43	144458.21	-9.82	-1416.59
EM DEBT	0.012	-3.71	2.02	0.275	-3.33	44.70	134030.73	-10.41	-1392.63
GLB GB	0.002	-3.03	2.20	0.374	-0.56	8.35	2248.38	-12.47	-1676.59
DM EQU	0.032	-10.44	8.41	0.977	-1.36	24.25	34482.07	-11.81	-1957.86
EM EQU	0.024	-6.47	4.96	0.987	-0.69	8.33	2279.41	-11.72	-1650.91
GLD	0.027	-5.86	4.97	0.879	-0.26	6.73	1064.69	-11.50	-1702.06
COMMD	0.010	-12.52	7.62	1.479	-0.89	11.84	6109.28	-11.15	-1933.00
ENRGY	0.004	-30.17	15.99	2.503	-1.46	23.33	31714.36	-11.59	-1922.34
AGG. DEBT	0.005	-2.20	1.53	0.299	-0.52	7.87	1864.80	-12.94	-1638.45
VIX	0.016	-29.98	76.82	8.440	1.30	10.04	4241.70	-13.59	-1734.61
FSI	-0.126	-573.01	506.05	33.274	0.02	104.53	774769.99	-12.48	-1526.20

Note: * Test at the 1% significance level. ** Indicates the lag value in the test.

Testing for stationarity conditions is necessary when extreme market conditions are present, as this is a precondition of the Cross-Quantilogram (CQ) method. For this purpose, the widely accepted Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were used to test stationarity. According to Uddin et al. (2019), although both tests are used to test whether variables have unit roots, the Phillips–Perron is a nonparametric test with autocorrelation and heteroscedasticity correction. The null hypothesis of the tests is that the variables are non-stationary, whereas the alternative hypothesis is that the variables are stationary. The test applied at the 1% significance level resulted in rejection of the null hypothesis and acceptance of the alternative hypothesis for all variables. Hence, the stationarity of the variables was determined.

¹ Calculated using the R package by Komsta, L. and Novomestky, F. (2022). moments: Moments, cumulants, skewness, kurtosis and related tests. *R package version, 14(1)*. <https://doi.org/10.32614/CRAN.package.moments>.

² Kurtosis, Jarque-Bera, ADF, and Phillips Perron tests calculated using the R package “tseries” Trapletti, A., Hornik, K. and LeBaron, B. (2023). tseries: Time Series Analysis and Computational Finance. *R package version 0.10-35*. <https://doi.org/10.32614/CRAN.package.tseries>

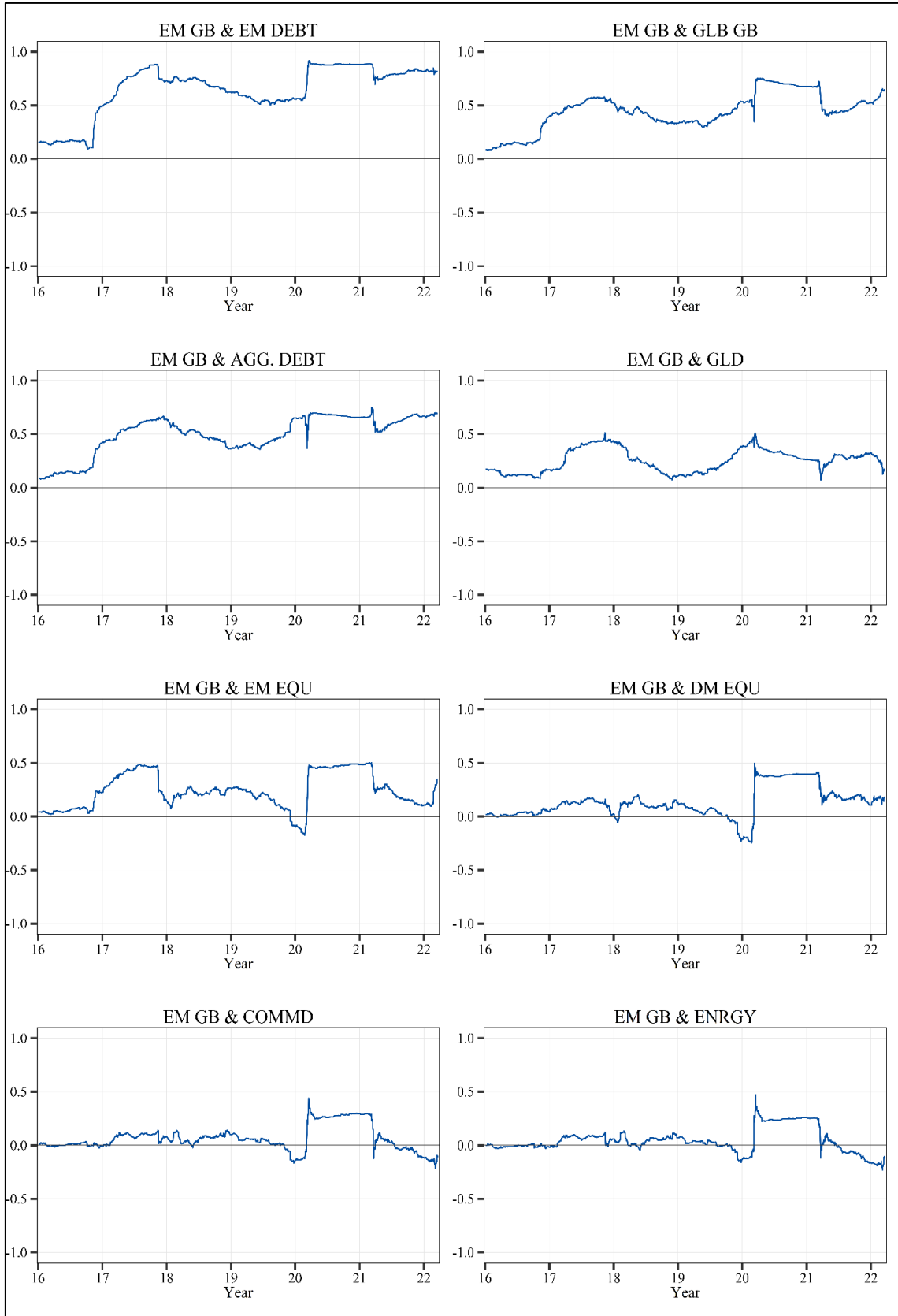


Figure 2. 252-day (one year) Rolling Correlation

Note: The correlation test indicates that EM Green Bonds have a growing correlation with other debt instruments.

The Jarque–Bera normality test, used to determine whether observations are normally distributed, revealed that the data distribution is not normal. This is consistent with the fact that price returns are typically not normally distributed (Fama, 1965). However, the observed non-normality indicated significant heterogeneity among the variables, as evidenced by the Jarque–Bera test, skewness, and kurtosis.

Regarding skewness, EM GB and debt securities had the highest negative skewness with negative values of 2.99 and 3.33, respectively. Negative skewness, also known as left skewness, implies that the left tail of the distribution is longer and extends in the negative direction, and the probability of negative values is higher than the probability of positive values. Conversely, right skewness implies that the right tail of the distribution is longer, also known as positive skewness. In a right-skewed distribution, the probability of a positive value occurring is higher than that of a negative value.

With negative skewness, DM equity and energy instruments exhibited the highest negative values after EM GB and EM debt instruments. However, the highest positive skewness of 1.3 was observed in the volatility index. Another measure of the normality of distribution was kurtosis. Kurtosis is used to measure the degree of steepness/kurtosis of the distribution. As the kurtosis coefficient moves away from zero in the positive direction, the distribution tapers. When it moves away from zero in the negative value direction, the distribution is kurtotic. A kurtosis coefficient of zero indicates that the distribution is normal in terms of kurtosis.

The abnormality of EM GB and general EM debt securities also stood out in terms of kurtosis. This is because these variables had the highest kurtosis (46.4 and 44.7, respectively) after the FSI and exhibit a pointed distribution. Energy and GP equity repeated the anomalous pattern in skewness and followed EM GB and EM debt securities with high kurtosis. However, the kurtosis coefficient for all the variables was higher than six. This means that the weight/thickness of the distribution tails was high and indicates more extreme price volatility than in the normal distribution.

Following Uddin et al. (2019), the rolling correlation between variables (one year–252 observations) and performance trends is visualized to present the data, as shown in Figures 2 and 3, respectively. Rolling correlations were calculated using the R software package developed by Ulrich (2021).

3.3. Trend and Performance

As shown in Figure 3 and Figure 4, the cumulative return (geometric) of the variables was calculated by indexing their prices to 100. The EM GB posted higher returns and lower volatility than the global GB both under normal and extreme market conditions in March 2020, when the COVID-19 pandemic emerged globally.

However, in the one-year period until early 2021, the performance of EM GB lagged behind that of the global GB. Equity markets in emerging and DMs, in contrast, offered higher returns to investors while requiring them to assume higher risks. In 2015, an investor investing \$100 (US) in EMs equity markets would have \$140 by the beginning of 2020.

The panic triggered by the COVID-19 pandemic eroded their gains and the investment value fell below the principal amount. By contrast, an investor who invested \$100 in EM GBs in

the same period had only \$125 by the beginning of 2020. When panic prevailed in the market in the following three months, the depreciation of this investor's investment remained relatively low, not exceeding 10%. The cumulative return was calculated using the R software package developed by Wuertz et al. (2023).

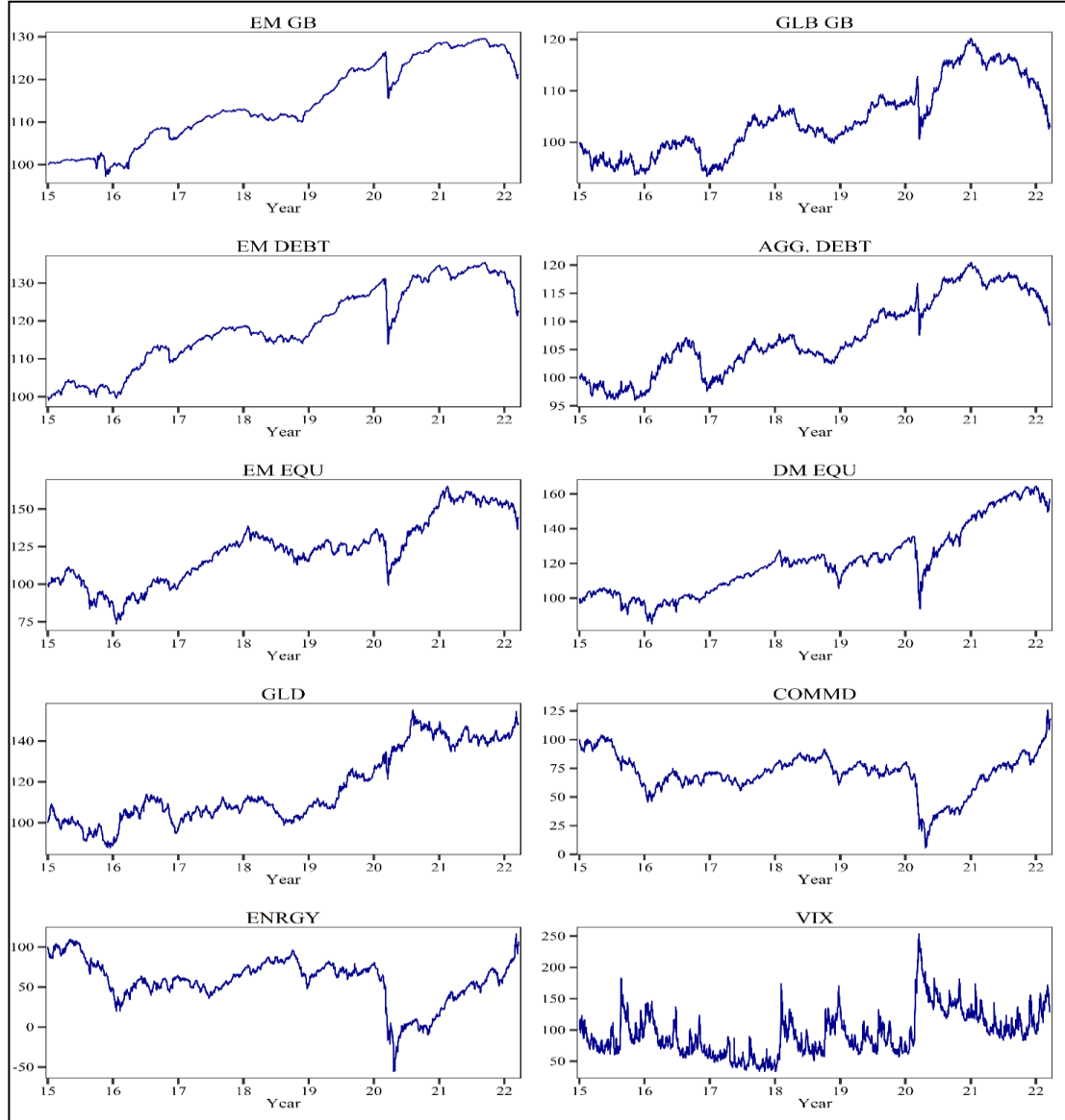


Figure 3. Trend and Cumulative Returns

Note: The prices of all variables are set to 100 on January 2, 2015, and the cumulative return (geometric cumulative return) is shown based on the natural logarithm of the daily price differences for the period covered in the study. The geometric cumulative return is calculated as follows Bacon (2004):

$$(1 + r_1) \times (1 + r_2) \times (1 + r_3) \times \dots \times (1 + r_{n-1}) \times (1 + r_n) = (1 + r)$$

By contrast, when compared to traditional debt instruments of EM, the EM GB yielded lower returns under normal market conditions. However, in extreme market conditions, for instance, during March 2020, EM GB exhibited higher resilience with less volatility, as

illustrated in Figures 5. The relative performance displayed in the chart was calculated using the method described by Peterson and Carl (2020) in the R software package.

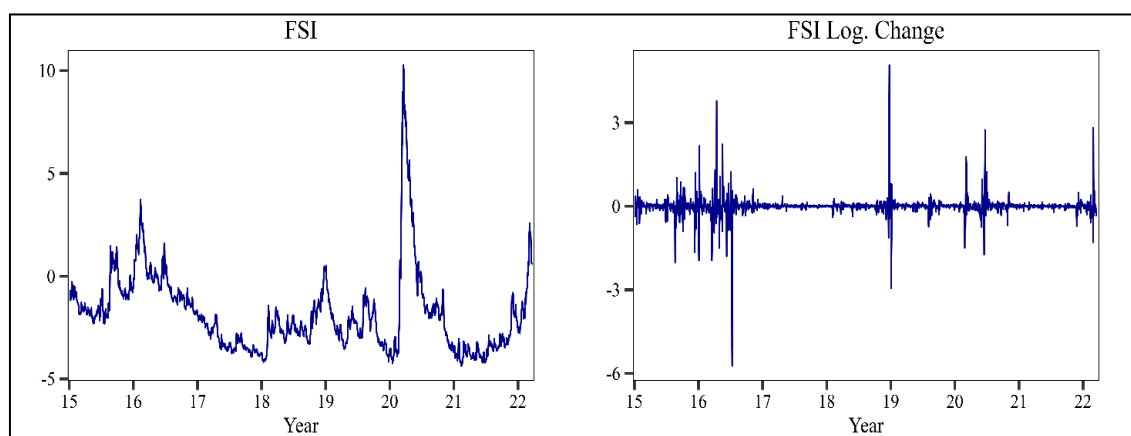


Figure 4. Financial Stress Index Performance

Note: Instead of presenting the performance and trend test in **Figure 3**, we show the daily price closures of the index on the left and the natural logarithmic price change used in the model on the right. This is because the Financial Stress Index is not well-suited for cumulative return calculation.

Further, compared to traditional EM debt instruments, the EM GB has delivered lower returns under normal market conditions. However, in extreme market conditions, such as the period between 2015 and 2016 and in 2020, the EM GB exhibited higher resilience with less volatility. This outlook is even better illustrated in Figure 5. The relative performance displayed in the chart is calculated using the methodology and R software package developed by Peterson and Carl (2020).

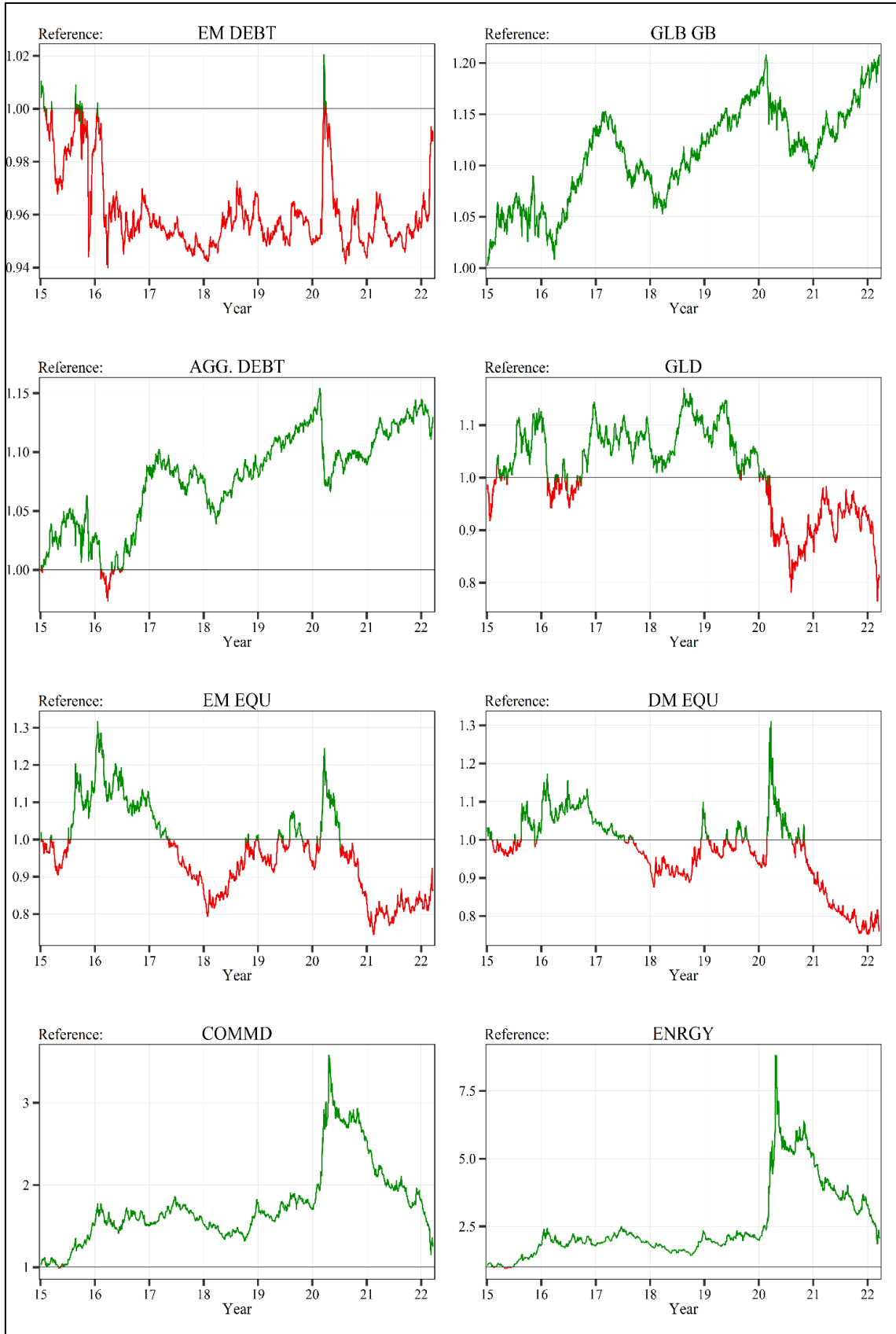


Figure 5. Relative Performance of Cumulative Returns

3.4. Methodology

This study applied the CQ method developed by Han et al. (2016). This method tests the correlation and dependence relationships between the two variables. Common tests typically measure variables from mean to mean. They divide the observations into a group or several groups and test by correlating the mean points of the groups (Uddin et al., 2019). Therefore, extreme values cannot be included, and the analyzed relationships cannot be fully revealed. By contrast, a feature of the CQ method is that the relationships tested are not only applied from mean to mean but also at various quantiles of the distribution; that is, at different probability values. Thus, different points (probability value quantiles) of the distribution, including the extreme values on the far right and far left in the distribution of the two linked variables, can be tested by associating them with the analysis at different lags. Another advantage of the method is that it tests the relationship by adjusting for macro conditions, such as volatility and financial stress (FS), through a Partial CQ [PCQ] (Han et al., 2016).

For the variables, we assume that y_t and x_t ($t \in \mathbb{Z}$) represent a stationary time series. Namely,

$y_t = (y_{1t}, y_{2t}) \in \mathbb{R}^2$ and $x_t = (x_{1t}, x_{2t}) \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$. Additionally, $x_{it} = [x_{it}^{(1)}, \dots, x_{it}^{(d_{it})}]^T \in \mathbb{R}^{d_i}$, $d_i \in \mathbb{N}$ for each $i = 1, 2$. In this case, the conditional distribution function for y_{it} is calculated as $F_{y_{it}|x_i}(\cdot | x_{it})$, assuming the density function of x_{it} is $f_{y_{it}|x_i}(\cdot | x_{it})$, and the conditional quantile function $q_{i,t}(\tau_i) = \inf\{v: F_{y_{it}|x_i}(v | x_{it}) \geq \tau_i\}$. Here, $\tau_i \in (0, 1)$, for each $i = 1, 2$. The two intervals between $(0, 1)$ of the symbol $\mathcal{T}$ are assumed to represent a cartesian product. This cartesian product can be represented as $\mathcal{T} \equiv \mathcal{T}_1 \times \mathcal{T}_2$. Here $\mathcal{T}_i$ comprises two values in the interval $0 < \underline{\tau}_i < \tilde{\tau}_i < 1$ and can be represented as $\mathcal{T}_i = [\underline{\tau}_i, \tilde{\tau}_i]$.

The CQ estimates the dependence relationship between two events/variables, represented as $\{y_{1t} \leq q_{1,t}(\tau_1)\}$ and $\{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$, by selecting a quantile q for each variable, at a quantile combination $\tau = (\tau_1, \tau_2)^T \in \mathcal{T}$ and a lag k . CQ starts with a process defined as the quantile-hit. Han et al. (2016) define the CQ as “the cross-correlation between two quantile-hit processes,” and is calculated as follows:

$$\rho_\tau(k) = \frac{E \left[\psi_{\tau_1} \left(y_{1,t} - q_{1,t}(\tau_1) \right) \psi_{\tau_2} \left(y_{2,t-k} - q_{2,t-k}(\tau_2) \right) \right]}{\sqrt{E \left[\psi_{\tau_1}^2 \left(y_{1,t} - q_{1,t}(\tau_1) \right) \right]} \sqrt{E \left[\psi_{\tau_2}^2 \left(y_{2,t-k} - q_{2,t-k}(\tau_2) \right) \right]}} \quad (2)$$

Han et al. (2016) propose dividing the time series into smaller samples by a process called resampling or bootstrap in the application of the method and calculation of the confidence interval. The CQ for the sample is as follows:

$$\hat{\rho}_t(k) = \frac{\sum_{t=k+1}^T \psi_{\tau_1} \left(y_{1t} - \hat{q}_{1,t}(\tau_1) \right) \psi_{\tau_2} \left(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2) \right)}{\sqrt{\sum_{t=k+1}^T \psi_{\tau_1}^2 \left(y_{1t} - \hat{q}_{1,t}(\tau_1) \right)} \sqrt{\sum_{t=k+1}^T \psi_{\tau_2}^2 \left(y_{2,t-k} - \hat{q}_{2,t-k}(\tau_2) \right)}} \quad (3)$$

In the resampling process, the method of Politis and Romano (1994) was used, following Han et al. (2016). The correction parameter used in this process was calculated using methods developed by Politis and White (2004) and Patton et al. (2009). The significance of the CQ test depends on whether the null hypothesis is rejected. The null hypothesis of this study is that the

relationship between the variables $\{y_{1t} \leq q_{1,t}(\tau_1)\}$ and $\{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$ is not different from zero in the quantile combination $\tau = (\tau_1, \tau_2)^T \in \mathcal{T}$ and lag k :

$$H_0: \rho_\tau(1) = \dots = \rho_\tau(p) = 0 \quad (4)$$

The alternative hypothesis is that at lag $k \in \{1, \dots, p\}$, there is a predictable relationship between the variables, and it is different from zero:

$$H_1: \rho_\tau(k) \neq 0 \quad (5)$$

The second stage of the research tested the adequacy of the results obtained with the CQ test to reject the null hypothesis. For this purpose, the Box–Ljung Q test (sup-version - sup-Q test)—also known as the Portmanteau test—was used, as suggested by Han et al. (2016). Box–Ljung is calculated as follows:

$$\hat{Q}_T^{(p)} \equiv T(T+2) \sum_{k=1}^p \hat{\rho}_\tau^2(k) / (T-k) \quad (6)$$

Hence, as visualized in Chart 11, the CQ value is set to zero in quantiles and lags, in which the null hypothesis cannot be rejected. We then apply the PCQ model derived from the CQ test to adjust for volatility (VIX) and financial conditions (FS), which represent uncertainty indicators. The PCQ is an extended CQ test for the variables $\{y_{1t} \leq q_{1,t}(\tau_1)\}$ and $\{y_{2,t-k} \leq q_{2,t-k}(\tau_2)\}$ to control for an environmental factor in the period between $\tilde{t}$ and $t-k$. For the control, $\mathbf{z}_t \equiv [\psi_{\tau_3}(y_{y_t} - q_{3,t}(\tau_3)), \dots, \psi_{\tau_l}(y_{lt} - q_{l,t}(\tau_l))]^T$ represents a numerical vector of the control variable $(l-2) \times 1$ with condition $l \geq 3$. Here, $q_{i,t}(\tau_i) = x_i^+ \beta_i(\tau_i)$, for τ_i and the vector $d_i \times 1$ is x_{it} ($i = 3, \dots, l$).

To calculate the partial CQ, the quantile-hit process is first applied, and the correlation matrix and deviated correlation matrix are obtained with the following PCQ model:

$$R_{\tilde{\tau}} = E[h_t(\tilde{\tau})h_t(\tilde{\tau})^T] \quad (7)$$

$$R_{\tilde{\tau}}^{-1} = E[h_t(\tilde{\tau})h_t(\tilde{\tau})^T]^{-1} = P_{\tilde{\tau}} \quad (8)$$

where $h_t(\tilde{\tau})$ represents the Quantile-Hit process and is defined as follows:

$$h_t(\tilde{\tau}) = [\psi(y_{1t} - q_{1,t}(\tau_1)), \dots, \psi_{\tau_l}(y_{lt} - q_{l,t}(\tau_l))]^T \quad (9)$$

Finally, the CQ dependence coefficient conditioned on the control variable $\mathbf{z}$ is obtained as follows:

$$\rho_{\tilde{\tau}|\mathbf{z}} = -p_{\tilde{\tau},12} / \sqrt{p_{\tilde{\tau},11}p_{\tilde{\tau},22}} \quad (10)$$

Since GBs are net receivers, they are treated as the dependent variable in the research, and the impact of other variables is the focus. In addition, the relationship between global and EM GBs is investigated bidirectionally. To implement the above stages, the “quantilogram” R software package developed by Oka (2022) is used.

In the research, 19 quantile values [$q = (0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, 0.95)$] are selected for each variable and tested in 361 quantile combinations. Following Uddin et al. (2019) and Pham (2021), the relationships between the variables included in the analysis are examined at four lags: daily, weekly,

monthly, and quarterly. In the analysis, the correlation and dependence relationship between the two variables tested in various quantiles are visualized in a heat map with the cross-quantile correlation (CQC) value according to the color value scale. Non-significant values are set to zero.

4. Results and Discussion

The findings of the test are revealed and discussed in two stages: CQC and PCQ, in which the test is repeated, controlling for market conditions.

4.1. Cross-Quantile Correlation: CQC

The results of the bidirectional dependence analysis between global GBs and GBs issued in EM are demonstrated in Figure 6. There is a significant but unequal relationship between these two assets in the short term, such as one day or one week. This is because the impact of the global GB on the EM GB is wider and lasts longer. Regarding the breadth of the effect, both positive and negative price movements in the global GB are directly proportional to the EM GB.

However, it is noteworthy that at high quantiles of 0.9, extreme appreciation of the global GB is not reflected in the EM GB. By contrast, extreme depreciation, represented by the low quantiles of the global GB, spills over to the EM GB and continues to negatively affect these bonds even a week later. Accordingly, the interdependent relationship between the global GB and the EM GB strengthens, and the pass-through increases during periods of extreme depreciation. The effect of depreciation in EM GBs is observed in global GBs the following day. However, unlike the effect of the global GB on the EM GB, this effect is very short and not seen after a week. Thus, EM GBs are positively dependent on short-term global GBs.

However, it is possible to say that the strongest impact on EM GBs does not stem from global GBs. As presented in Figure 7, the short-term impact of the dollar (US) denominated conventional debt instruments of EM DEBT on EM GBs is evident and stronger in all quantiles. This effect is particularly strong during periods of negative returns. Since the EM GB is a debt instrument in EMs, this dependency relationship can be understood.

The global-aggregate debt market (AGG DEBT) exhibits an effect similar to that of global GBs. Although the global debt market proportionally affects EM GBs in most quantiles, the excessive appreciation in higher quantiles is not reflected in EM GBs. However, a striking detail in the effect of the global-aggregate debt market is seen in the one-month lagged effect. Namely, when the EM GB is in the middle cantilevers, that is, in periods when it is stable and does not show a large movement, the movements in the global debt markets are reflected in the EM GB in a low but negatively proportional manner one month later. In particular, one month after a moderate depreciation in general debt instruments, limited and mild reflections in the opposite direction are observed for the EM GB.

Regarding the relationship between EM GBs and equity markets, EM GBs have a dynamic dependency relationship with the equities of both emerging and DMs, which vary across maturities and quantiles. When analyzed in terms of EM equity, there is a positive spillover from EM equity to EM GBs, except for the periods when EM equity generates excessively positive returns and EM GBs generate static or negative returns.

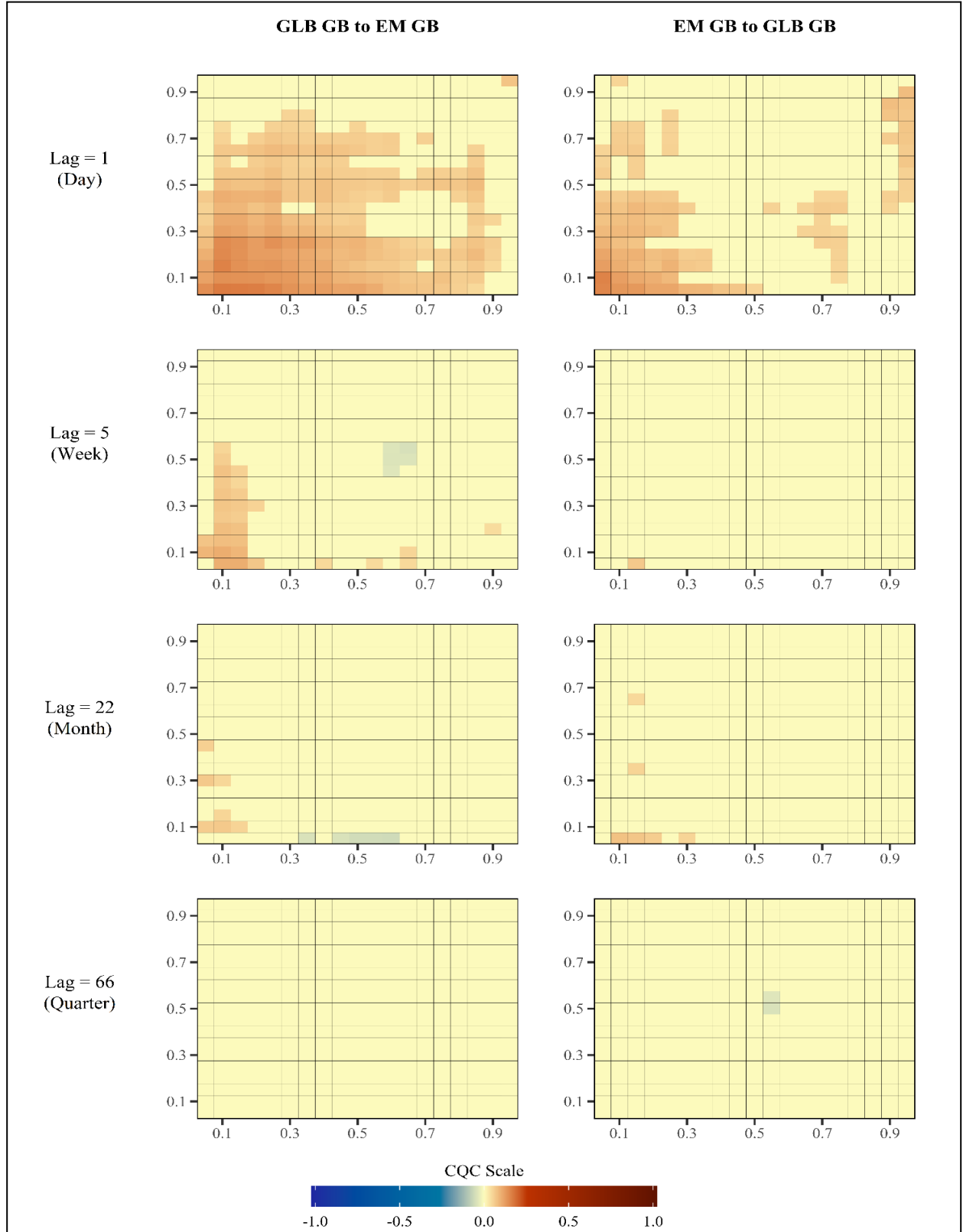


Figure 6. CQ Interdependence between Global GB and EM GB

Note: The independent variable is represented on the vertical axis, while the dependent variable is represented on the horizontal axis. The graph displays the relationship between the independent and dependent variables. The numerical values on the axes indicate the quantile values of the distribution. The CQC values are color-coded based on the value scale. Statistically insignificant results have been set to zero.

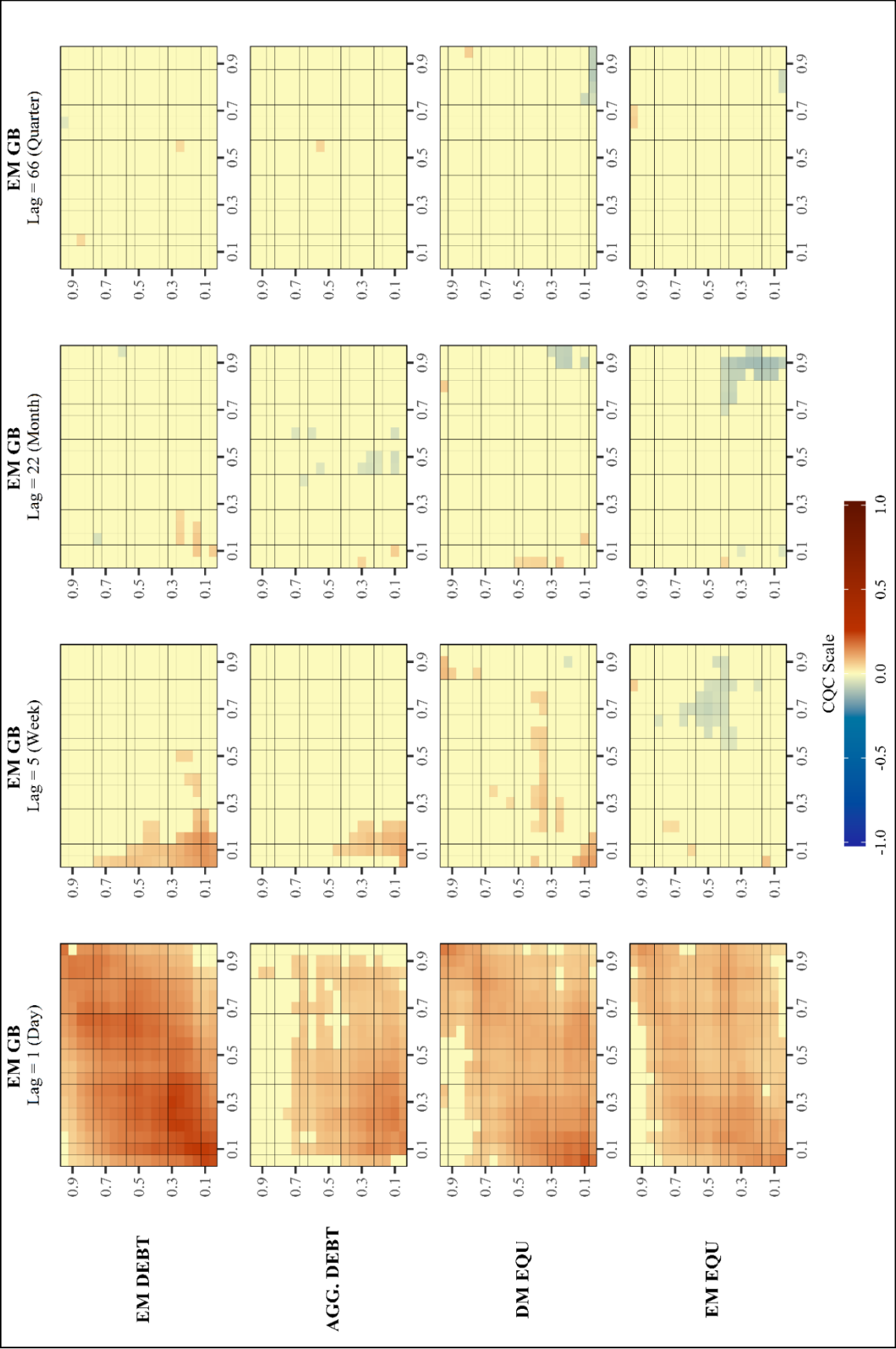


Figure 7. The Dependency of EM GB on Debt and Equity Markets

However, at a one-week time window, this spillover turns into an opposite and more limited effect. What is meant by more limited is that this effect is seen in fewer quantiles. This is because there is no negative dependence in periods when EM equity is stable, and EM GBs are positive. This negative relationship persists for one month later. However, this one-month lagged effect is limited to periods when EM GBs are extremely positive, and EM equity yields negative returns.

Nevertheless, the effect of the DM equity market in the very short term, such as one day, seems stronger than that of EM equity. This effect is even stronger during periods of high volatility; that is, during periods of extreme positive or negative values. However, compared to DM equity, the effect of DM equity on weekly and monthly maturities is complex and weaker. At one-day maturity, EM GB has a positive dependence on both DM and EM equity markets. The effect of the DM share is stronger at this maturity and disappears at longer maturities. By contrast, the effect of EM share turns negative and weakens but persists for a longer period.

Figure 8 demonstrates the analysis results of the dependence of the EM GB on gold, energy commodities, and commodity markets in general. At a one-day time window, EM equity is generally positively dependent on gold, except in periods of extremely positive returns. Conversely, the dependence of EM GB on commodity markets is limited to periods of extremely negative returns. At a one-month time window, there is a weak negative dependence relationship that varies across the quantiles.

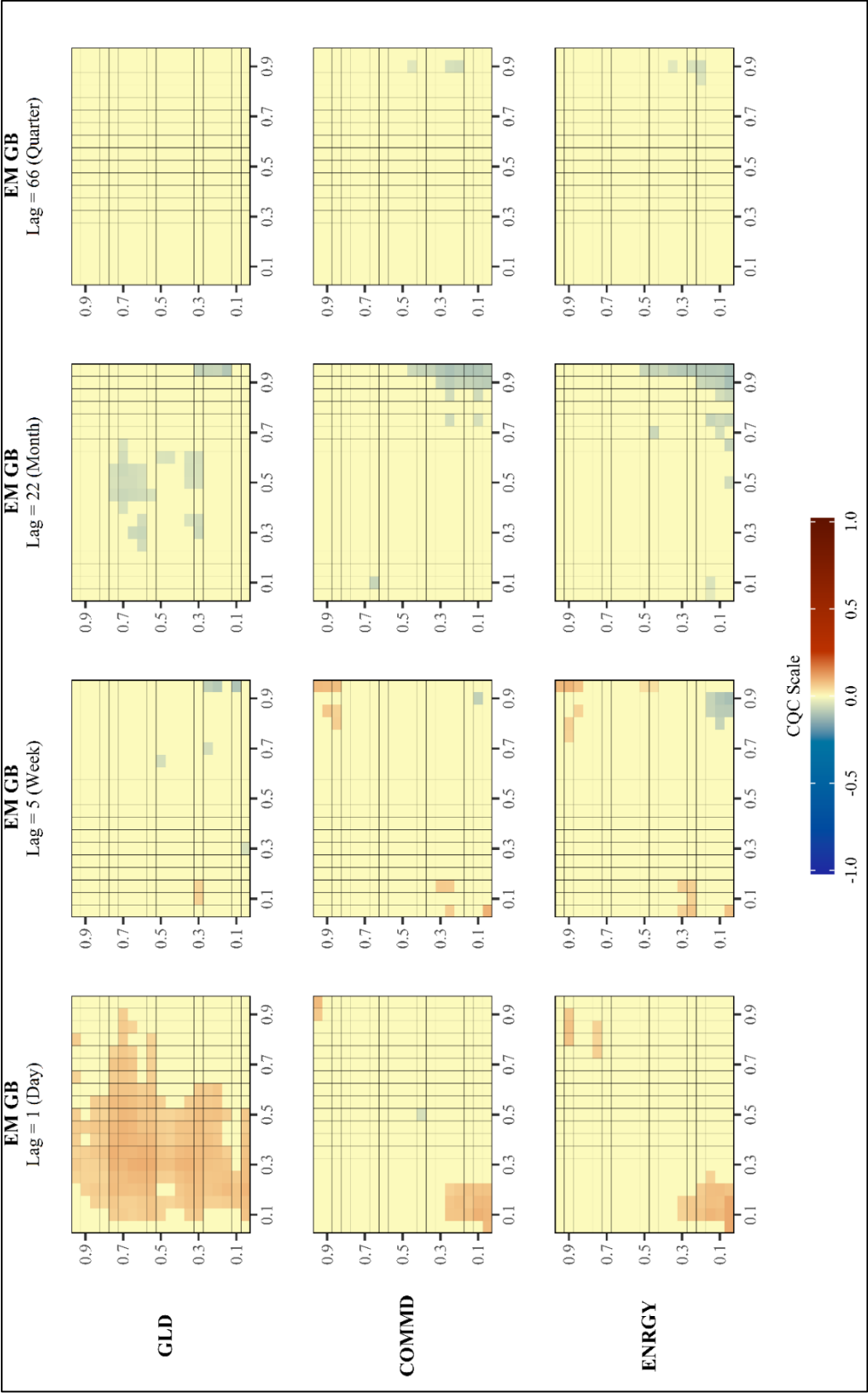


Figure 8. Dependency of EM GB on Gold, Commodity, and Energy Markets

4.2. Control for Market Conditions: PCQ

In situations in which uncertainty and/or the perception of uncertainty are prominent, the dependence relationship between variables may change as investors' views and preferences change. For example, Pham (2021), who analyzed the relationship between GBs and green stocks, stated that although there is a weak dependence relationship between the variables under normal market conditions, this dependence strengthens under extreme market conditions and rises and falls together. Therefore, it is useful to include uncertainty (environmental) as a control variable in the analysis and repeat the test. In the control test, the PCQ described in the methodology section was applied. The variables selected as uncertainty indicators were considered to have a quantile value of 0.90. Although daily, weekly, monthly, and quarterly lags were investigated in this study, a PCQ test was applied only for daily and monthly lags because of its salience. Controlling for volatility (VIX index) and FS, a proxy for financial conditions—the CQC between global GBs and EM GBs—did not change significantly, except for dependence spanning several quantiles. This result indicates that the positive dependence relationship between EM GB and global GB is insensitive to market conditions (Figure 9). From an investor perspective, this result implies that there is no hedging value in buy–sell transactions because of the direct correlation between very short-term EM GB and global GB. The same result implies that an investor who holds a global GB in their medium/long-term portfolio can hold some EM GB without disturbing portfolio diversification.

A similar pattern is observed for the dependence of EM GBs on other debt instruments. When extreme market conditions are controlled, the dependence of EM GBs on EM DEBT and debt instruments in general, as represented by AGG DEBT, did not change significantly (Figure 10). However, the situation differs in terms of the dependence of the EM GB on equity instruments.

As market uncertainty is controlled, the negative impact of the EM GB on the dependency relationship with equity instruments in the medium term, such as one month, is strengthened by spreading to more quantiles. This negative dependency relationship of EM GB is especially valid for EM equity. When the impact of the latter is compared to that of DM equity on EM GB, the impact of EM equity is more pronounced.

However, there was no significant change in the CQC of either equity instrument at a one-day lag. These findings indicate a medium-term negative correlation between EM GB and equity instruments, which weakens during periods of uncertainty. Here, the very short-term direct correlation between EM GB and equity instruments, such as one day, may be attributed to cross-market volatility. The longer-term negative correlation can be attributed to economic fundamentals.

These findings suggest that investors holding DM equity assets in their portfolios may diversify by investing in the EM GBs. Investors investing in EM equity markets, in contrast, reduce their portfolio risk by investing in green bond instruments in EMs while making additional investments in these countries.

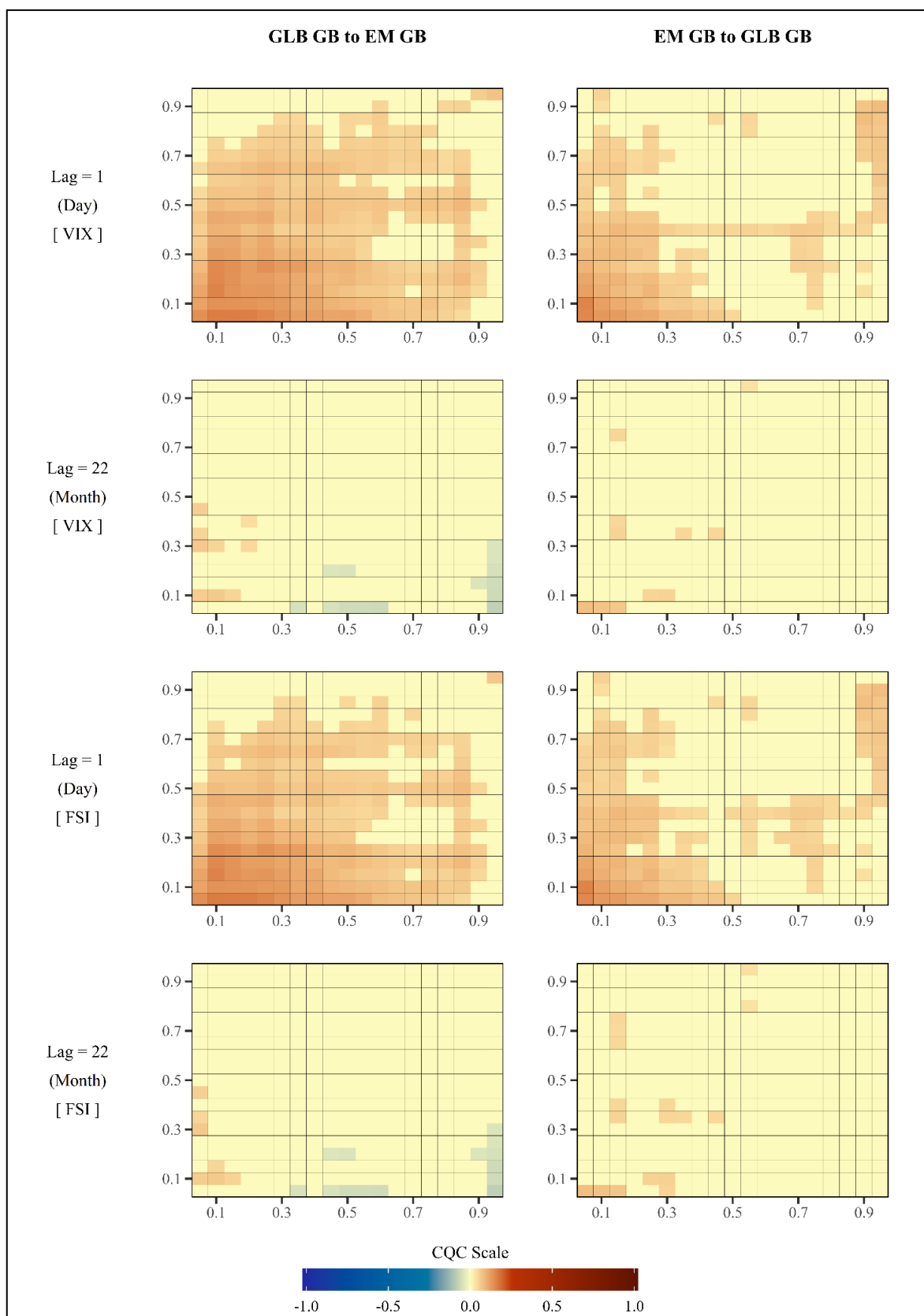


Figure 9. Interdependence Between Global GB and EM GB After Controlling for Market Conditions—PCQ

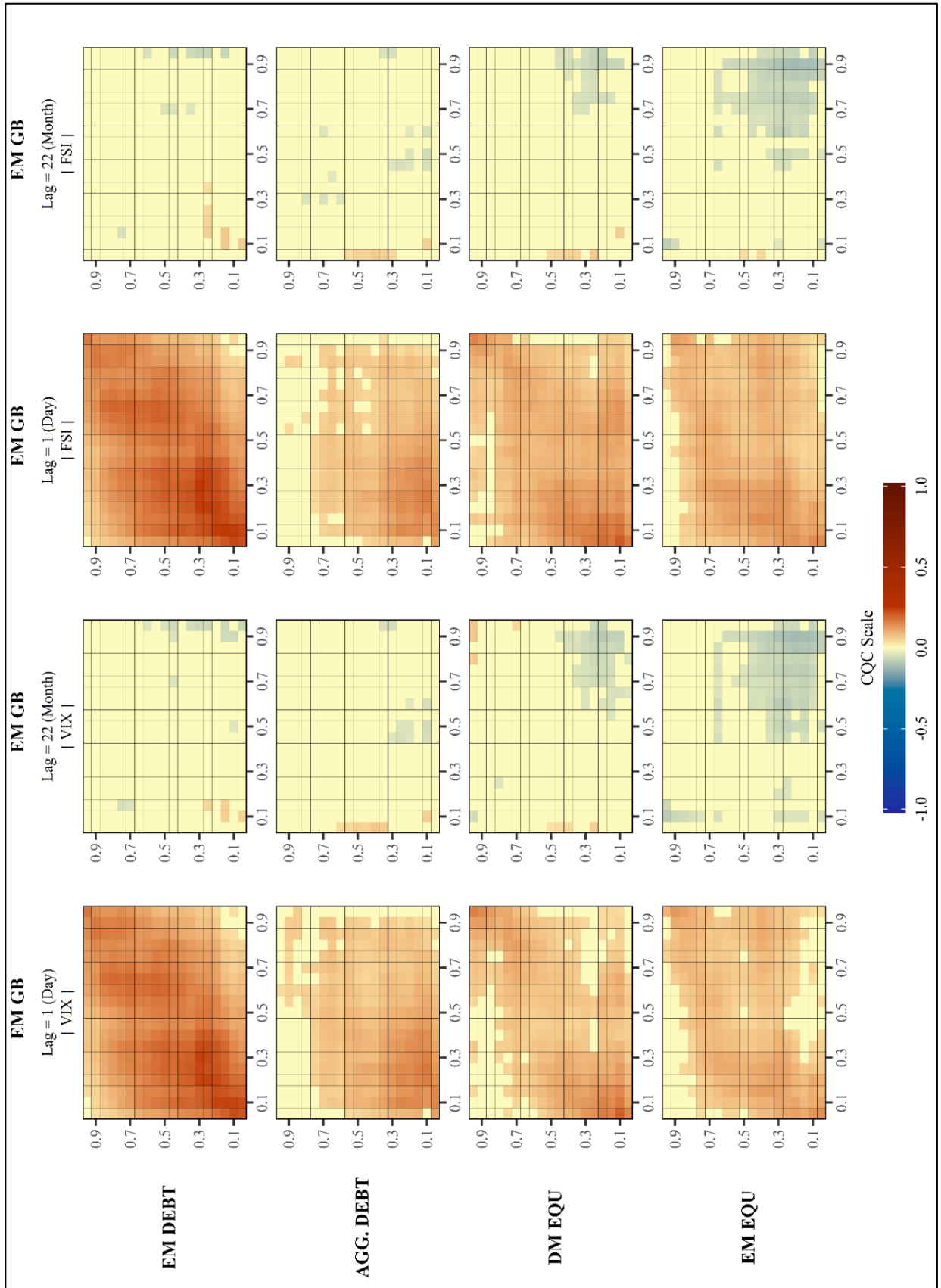


Figure 10. Dependency of EM GB on Debt and Equity Markets After Controlling for Market Conditions

Finally, the relationship between EM GBs, gold, and commodities can be analyzed. When market conditions are controlled for in Figure 11, the positive effect of gold in the very short term slightly increases. There is no significant change at one-month maturity. When gold is in the mid-quantiles, that is, when it exhibits its usual volatility, this volatility is reflected in the EM GB in the opposite direction one month later. In general, except for the very short term, the gold–EM GB relationship does not show a remarkable change according to market conditions.

However, the commodity to EM GB relationship is open and dynamically dependent on volatility and financial conditions. This is especially true for longer maturities, such as one month. While the dependence of EM GB on commodity instruments is weak and limited to a few quantiles with a one-month lag in the CQ test, a significant negative correlation emerges when financial conditions are controlled for in the PCQ test.

The negative dependence of EM GB on both the general commodity market and energy commodities is similar. This is because the moderate and slightly positive volatility of these commodities is generally reflected negatively in the EM GB. Similarly, when the EM GB is extremely positive, the depreciation in these assets is reflected in the opposite direction and supports the positive mobility of the EM GB. However, unlike the general commodity market, whose excessive negative volatility is not reflected in the EM GB, energy commodities impact the dependent variable at their lowest quantiles of 0.05–0.15, meaning that excessive depreciation of energy commodities is reflected in the EM GB in the opposite direction and increases its return. These findings on the dependence of EM GB on commodity instruments shed light on important diversification potential and may have positive implications for investors and EM GB issuers.

4.3. Policy Implications and Regulatory Outcomes

The findings of this study offer critical regulatory implications for the development and oversight of the Green Bond (GB) market in Emerging Markets (EMs). The most significant observation is the presence of a high and often instantaneous contagion risk between EM GBs and nearly all other asset classes examined, including conventional debt and equity markets. This outcome fundamentally challenges the notion of EM GBs as isolated assets and signals a vulnerability from the perspective of financial stability. These findings result in several concrete policy implications and recommendations for regulators tasked with maintaining financial stability and overseeing the development of sustainable finance in emerging economies.

1. **Systemic Risk Monitoring Enhancement:** Given the intensity of risk spillovers—particularly the asymmetric negative shocks propagating from global markets to EM GBs during periods of extreme depreciation—EM regulatory authorities must establish enhanced systemic risk monitoring mechanisms. These systems must be designed to meticulously monitor and oversee these channels of instantaneous contagion, with the objective of averting any potential market disruption.

2. **Proactive Financial Regulations:** The strong interdependence found suggests that regulators should not treat green financial instruments as inherently risk-decoupled. Instead, it is imperative that they consider the implementation of proactive financial regulations, such as adequate capital buffers or liquidity requirements. These regulations are designed to shield EM capital markets from external shocks that rapidly transmit via the green bond segment.

3. An In-Depth Analysis of Risk Transmission: In light of the anticipated sustained expansion of the EM GB market, it is imperative for regulatory authorities to conduct a meticulous examination of the underlying risk transmission mechanisms. This research should aim to specifically identify the threats posed by these mechanisms to financial stability, thereby enabling the development of targeted, preemptive, and sector-specific regulations to minimize systemic exposure.

4. Integrating Green Instruments into Stability Frameworks: The study's findings indicate that the financial behavior of EM GBs is significantly influenced by the broader conventional EM financial system. Consequently, regulatory authorities must acknowledge that the "green" label does not inherently mitigate financial contagion risk. Consequently, the integration of green financial instruments within the prevailing financial stability framework is imperative, as opposed to their treatment as discrete entities, which are perceived as lower risk.

4.4. Practical Implications and Investment Strategies

The findings of this study offer concrete strategic implications for portfolio managers and international investors targeting Emerging Markets. The analysis indicates that Emerging Market Green Bonds (EM GBs) possess a multifaceted and evolving value with respect to the objectives of portfolio diversification and hedging. The intricate dependencies observed across different asset classes have significant consequences for investment strategy, portfolio construction, and risk management. These consequences can be enumerated as follows:

1. The present study explores the limited substitution and diversification value in debt. An examination of the observed high and direct correlation between EM GBs, global GBs, and conventional USD-denominated EM debt instruments indicates that EM GBs do not exhibit independent movement in their risk-return profile. Consequently, investors should regard EM GBs as a substitute product within the debt segment, offering limited incremental diversification benefit to an existing bond portfolio. The elevated contagion risk further accentuates the constrained capacity of EM GBs to mitigate overall portfolio risk, particularly during periods of market stress.

2. Medium-Term Diversification Potential: Despite the short-term contagion effects, the dynamic dependency relationship between EM GBs and equity markets suggests a crucial role in the medium-term portfolio horizon. EM GBs offer the potential for diversification and risk reduction against equity exposure. Portfolio managers would be wise to consider a strategic allocation to EM GBs in order to balance the volatility inherent in EM equity markets. This would require a recognition of their value as a counterweight over a longer timeframe.

3. Hedging Effectiveness against Commodities: The study identifies a differentiated relationship between EM GBs and commodity markets. While a robust positive correlation with gold is evident, a negative proportional relationship with broader commodity markets becomes apparent under standard market conditions. This particular negative correlation offers a strategic insight: EM GBs have the potential to function as an effective hedging instrument against risks stemming from commodity price fluctuations, thereby contributing a distinctive value to a multi-asset portfolio.

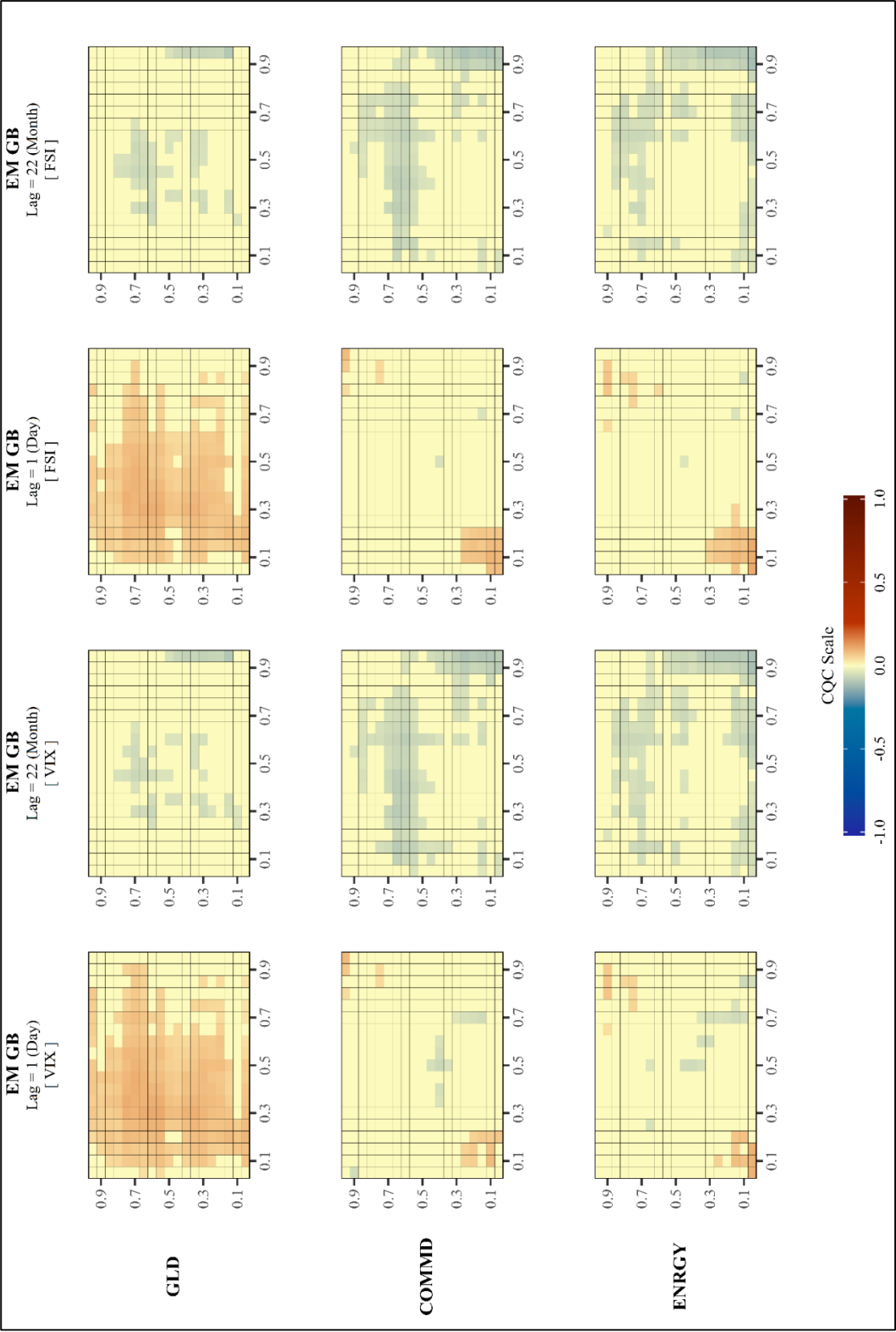


Figure 11. Dependency of EM GB on Gold, Commodity, and Energy Markets After Controlling for Market Conditions

5. Conclusion

The total amount of GSS Bonds exceeded USD 4 trillion in the first half of 2023. Although the issuance of GBs has increased rapidly in developing countries, it has not exceeded one in five of the cumulative issuances of GBs.

Some problems related to sustainability and GBs, such as transparency, accounting, and auditing, persist. In the GBs of developing countries, the lack of clarity on risk, return, and portfolio value, because these instruments are not yet widespread, poses an additional problem for investors. It is foreseeable that the GB markets of emerging economies will grow in line with current market trends and international policies. Therefore, eliminating uncertainties regarding these instruments will be beneficial for both investors and issuers.

Although there is a large body of literature analyzing the relationship between GBs and other asset classes, studies on GBs generally use global GB indices, particularly the S&P GB index and the Barclays Bloomberg GB index, as representatives of GBs. These global indices cover investment-grade GBs in both developed and developing countries. The fact that these instruments are mostly issued in DMs has led DMs to dominate global GB indices. Thus, global GB indices do not reflect the performance of GBs issued in EMs.

To find an answer to this gap in the literature, the J.P. Morgan GB Emerging Markets 10% Country Cap index, which covers only GBs issued in EMs, is taken as an indicator of the EM GB market, and the relationship between this market and other asset classes is investigated. Using daily price data for the period between 2015 and 2022, the relationship between EM GBs and global GBs; EM and global debt instruments, developed and EM equity instruments, and gold, commodity, and energy markets is tested using the CQ method.

The current results contribute to the literature and provide important implications for both financial market regulators and international portfolio investors. In the findings, high contagion, which poses a threat to financial stability in terms of regulatory and supervisory institutions, has been found, while results of interest to international portfolio investors in terms of risk and portfolio diversification have been reached.

The findings are of considerable significance for regulators in emerging markets. The high and instantaneous contagion risk from global markets to EM Green Bonds fundamentally challenges the perception of these instruments as isolated or inherently safer. Consequently, authorities should refrain from perceiving the "green" label as a mitigator of financial risk. It is imperative to integrate green financial instruments fully into systemic risk monitoring and mainstream financial stability frameworks. Proactive measures such as enhanced capital buffers may be implemented to shield against external shocks. These measures should be considered in lieu of managing them as a separate, lower-risk asset class.

For portfolio managers and international investors, the ramifications are both strategic and multifaceted. Our analysis indicates that EM Green Bonds offer limited diversification benefits within a fixed-income portfolio, acting more as a substitute for conventional EM debt due to high correlation. Nevertheless, they offer a significant opportunity for medium-term diversification against the volatility of EM equities. Moreover, their negative correlation with broader commodity markets suggests that they can serve as an effective hedging instrument against commodity price fluctuations, thereby adding a distinct value to a multi-asset portfolio.

Financial market regulators should consider the high degree of pass-through between the one-day short-term EM GB and other markets. This contagious risk pass-through between the EM GB and almost all other markets poses a problem for regulators who aim to reduce the total risk in the market and prevent financial crises. High contagion across markets, especially when panic prevails, may jeopardize financial stability. Therefore, the risk transmission mechanisms of EM GB instruments discussed in this study, which are expected to continue to grow in the future, should be further investigated, and the threats posed by these transmission mechanisms on financial stability should be identified and minimized.

Regarding portfolio diversification, the findings regarding EM GB can be summarized under three headings: debt instruments, equities, and commodities. Among debt instruments, the fluctuations observed in the total debt instruments of EMs and global GBs are reflected in the EM GB in a directly proportional manner, and this effect disappears as maturity increases. While this result shows that these instruments cannot be used to hedge against each other, the disappearance of the dependency relationship in the long run requires further investigation. Although basic economic and financial logic assumes that the dependence between these assets will continue to some extent in the long run, the analysis shows a weak relationship in the long run. This leaves a gap in the literature that needs to be addressed.

There is a dynamic dependence relationship between EM GBs and EM equity. In the very short term, there is generally a positive spillover from EM equity to the EM GB, but this turns into an inverse and more limited effect in the one-week term. This negative relationship persists after one month.

After controlling for market conditions, there is no significant change in the CQC between equity instruments and EM GBs with a one-day lag, but the negative relationship strengthens with a one-month lag. These findings indicate that there is a medium-term negative correlation between EM GBs and equity instruments, but this relationship weakens during periods of uncertainty. There is a negative correlation between EM GBs and equity instruments in the medium term under normal market conditions. When excessive volatility exists in the market, the negative relationship weakens and becomes more neutral.

This result suggests that investors holding equities in their medium-term portfolios can diversify and reduce portfolio risk by investing in the GBs of EMs. This is particularly true for equity instruments in EMs. Thus, investors who invest in equities in these markets reduce their portfolio risk while making additional investments in these countries without reducing their equity investments.

Usually, there is a positive correlation between gold and EM GBs in the very short term of one day. When market conditions are controlled for, the positive effect of gold in the very short term increases slightly. In the one-month term, there is no significant change. The gold–EM GB relationship does not change significantly according to market conditions. This result points to a diversification potential between gold and EM GBs, but this relationship needs to be further investigated.

As for the dependence of EM GBs on commodity markets, in the short term, the pass-through from other markets to EM GBs is minimal in commodity markets. In the medium term, there is an open and dynamic dependence on market conditions. This is because the CQ test does not reveal a significant relationship, whereas a significant negative relationship emerges

when controlling for market conditions. Slight to moderate positive price movements in the energy and general commodity markets are generally negatively correlated with GBs. Similarly, while GBs are positive, depreciation in these assets is reflected in EM GBs in the opposite direction and supports their positive volatility.

These findings on the dependence of EM GBs on commodity instruments shed light on important diversification potential and may have positive implications for GB investors and EM GB issuers in EMs. This study leaves several research topics for future research. First, as mentioned above, the risk transfer mechanisms related to EM GB instruments should be analyzed in more detail, and the possible negative effects on financial stability should be investigated.

Second, some uncertainty remains in the medium- and long-term relationships of EM GBs with other debt instruments. Therefore, unanswered questions remain until the interdependent relationships between these assets are tested with other methods and more comprehensive inputs. The third research issue is that although the methodology used in this study provides some advantages in testing interdependence relationships, it does not include risk–return performance indicators in the analysis; therefore, comparative performance analysis with interdependence relationships should be performed in studies aiming at portfolio optimization. Finally, the growth of GB markets in EMs may eliminate some of the study limitations, and it would be useful to retest the relationships discussed in this study with more favorable inputs.

Declaration of Research and Publication Ethics

Ethics committee approval and/or legal/specific permission are not required for this study, which complies with research and publication ethics.

Researcher’s Contribution Rate Statement

The authors declare that they have contributed equally to this article.

Declaration of Conflict of Interest

The authors declare that they have no potential conflict of interest.

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APPENDIX

Table A1. Dates of “J.P. Morgan Green Bond Emerging Markets 10% Capped Index” price data interruptions.

19/01/2015	18/01/2016	16/01/2017	19/02/2018	18/02/2019	17/02/2020	15/02/2021
16/02/2015	15/02/2016	20/02/2017	30/03/2018	19/04/2019	10/04/2020	02/04/2021
03/04/2015	25/03/2016	14/04/2017	28/05/2018	27/05/2019	25/05/2020	31/05/2021
25/05/2015	30/05/2016	29/05/2017	04/07/2018	04/07/2019	03/07/2020	05/07/2021
03/07/2015	04/07/2016	04/07/2017	03/09/2018	02/09/2019	07/09/2020	06/09/2021
07/09/2015	05/09/2016	04/09/2017	08/10/2018	14/10/2019	12/10/2020	11/10/2021
12/10/2015	10/10/2016	09/10/2017	12/11/2018	11/11/2019	11/11/2020	11/11/2021
11/11/2015	11/11/2016	23/11/2017	22/11/2018	28/11/2019	26/11/2020	25/11/2021
26/11/2015	24/11/2016	25/12/2017	25/12/2018	25/12/2019	25/12/2020	24/12/2021
25/12/2015	26/12/2016	01/01/2018	01/01/2019	01/01/2020	01/01/2021	17/01/2022
01/01/2016	02/01/2017	15/01/2018	21/01/2019	20/01/2020	18/01/2021	21/02/2022

THE TRANSITION TO AN IMPACT-BASED APPROACH IN SUSTAINABILITY AND FINANCIAL REPORTING

Sürdürülebilirlik ve Finansal Raporlamada Etki Temelli Yaklaşım Geçiş

Ayşenur TARAKCIOĞLU ALTINAY^{*ID}, Barış SARDOĞAN^{**ID}

Abstract

This paper analyzes the paradigm shift in sustainability and financial accounting on a sample of the first 100 companies reporting under the European Union's Corporate Sustainability Reporting Directive (CSRD). Drawing on the shift from financial-focused reporting to impact-based disclosures, the study concentrates on the use of materiality and double materiality concepts developed by ESRS. Through a review of the world practices in these early adopters, the research also elicits patterns and challenges that firms face, as well as wider strategic implications involved with ESG considerations for corporate reporting. It emerged from the findings that there is considerable diversity in double materiality interpretation, indicating a lack of consistency and comparability despite regulatory guidance. The analysis also highlights the importance of harmonized standards to increase transparency, trust from stakeholders, and sustainable value creation. By harmonizing between classical financial and the impact-based sustainability reporting, this study delivers implications for researchers, regulators, as well as standard setters and professionals and practitioners interested in companies' reporting in the age of CSRD ESRS. Ultimately, the study contributes to a deeper understanding of how early adoption of CSRD reporting shapes corporate accountability, decision-making processes, and the measurement of long-term ESG impacts.

Keywords:

Sustainability,
Corporate
Sustainability
Reporting Directive,
European
Sustainability
Reporting Standards,
Environmental Social
and Governance,
Energy Sector.

JEL Codes:

Q56, M41, M49.

Öz

Bu makale, Avrupa Birliği Kurumsal Sürdürülebilirlik Raporlama Direktifi (CSRD) kapsamında raporlama yapan ilk 100 şirketin örnekleminde yola çıkarak sürdürülebilirlik ve finansal muhasebedeki paradigma değişimini analiz etmektedir. Finansal odaklı raporlamadan etki temelli açıklamalara geçişten yola çıkan çalışma, ESRS tarafından geliştirilen önemlilik ve çift önemlilik kavramlarının kullanımına odaklanmaktadır. Bu erken benimseyenlerin dünya uygulamalarını inceleyerek, araştırma aynı zamanda şirketlerin karşılaştığı kalıpları ve zorlukları ve kurumsal raporlama için ESG hususlarıyla ilgili daha geniş stratejik etkileri ortaya koymaktadır. Bulgular, çift önemlilik yorumunda önemli bir çeşitlilik olduğunu ortaya koymuş ve bu da düzenleyici kılavuzlara rağmen tutarlılık ve karşılaştırılabilirlik eksikliğini göstermektedir. Analiz ayrıca şeffaflığı, paydaşların güvenini ve sürdürülebilir değer yaratmayı artırmak için uyumlaştırılmış standartların önemini vurgulamaktadır. Klasik finansal raporlama ile etki temelli sürdürülebilirlik raporlamasını uyumlu hale getiren bu çalışma, CSRD ESRS çağında şirketlerin raporlamasıyla ilgilenen araştırmacılar, düzenleyiciler, standart belirleyiciler, profesyoneller ve uygulayıcılar için çıkarımlar sunmaktadır. Sonuç olarak, bu çalışma, CSRD raporlamasının erken benimsenmesinin kurumsal hesap verebilirliği, karar alma süreçlerini ve uzun vadeli ESG etkilerinin ölçülmesini nasıl şekillendirdiğine dair daha derin bir anlayışa katkıda bulunmaktadır.

Anahtar Kelimeler:

Sürdürülebilirlik,
Kurumsal
Sürdürülebilirlik
Direktifi,
Avrupa
Sürdürülebilirlik
Raporlama
Standartları,
Çevresel
Sosyal ve
Yönetimsel,
Enerji Sektörü.

JEL Codes:

Q56, M41, M49.

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1. Introduction

Corporate reporting systems have been evolving rapidly in response to global sustainability imperatives and changing stakeholder expectations over the last decade. The EU’s Corporate Sustainability Reporting Directive (CSRD) and the European Sustainability Reporting Standards (ESRS) associated with it move from financial to impact disclosure. This shift challenges the way in which companies think about materiality, accountability, and value creation. It shifts corporate reporting from a compliance exercise into integrating sustainability information into decision-making processes and connecting environmental and social outcomes with business value.

The transformation of this regulatory shift is well-documented, but the academic knowledge on it is piecemeal. Previous studies of sustainability reporting have mainly focused on voluntary disclosure standards such as GRI or SASB and frequently concentrated on a high-level evaluation of quantity or quality environmental, social, and governance (ESG) indicators, instead of the theoretical constructs that underpin disclosure discretion.

Double Materiality introduced under CSRD, for reports covering both financial and impact materiality, not only constitutes a new reporting architecture but also sets up conceptual challenges calling for scholarly interpretation. The contested nature of materiality has been acknowledged in extant literature (Oll et al., 2025); yet, despite this inherent resistance of the concept, very few studies connect to that debate as well as to wider theories on organizational legitimacy and stakeholder accountability.

The theorization of the institutionalization of sustainability reporting can take several perspectives. Stakeholder theory (Freeman, 1984) helps to predict why firms would be responsive to society and investor calls for transparent sustainability. According to legitimacy theory (Suchman, 1995), disclosure is viewed as an approach to fostering and maintaining organizational legitimacy in the face of regulatory and social pressure. Signaling theory (Spence, 1973) offers an interpretation for how sustainability disclosures signal credibility and responsibility to external parties.

Both frameworks allow for a more sophisticated understanding of how firms reconcile the conflicting demands of regulatory compliance with reputational differentiation in the post-CSRD era. Yet despite this profusion of policy debate, empirical academic understanding about how real-world companies implement double materiality is scarce. The majority of the existing literature has been concentrated on normative and/or descriptive aspects of ESRS, rather than its real-world application or theoretical significance.

Against this background, the present study contributes to existing research by providing empirical insights into the first 100 so-called corporate sustainability reports issued under the CSRD regime in order to ascertain how early adopters interpret, structure, and disclose materiality assessments. Therefore, the study is underpinned by the following primary research question:

What sectors and concepts characterize early CSRD adopters when it comes to the (application of) double materiality in sustainability reporting?

In tackling this topic, the studies aim to narrow the distance between regulatory evolution and academic theorizing. It tries to clarify the interrelations between policy design and corporate behavior, adding empirical evidence to ongoing debates within the field of sustainable accounting. The results of the study may illuminate the impact of reporting as a tool for legitimacy, stakeholder participation, and sustainable value source.

2. Conceptual Framework

2.1. From Financial to Impact-Based Reporting

The evolution from traditional financial disclosure toward sustainability-oriented reporting marks a fundamental shift in corporate communication and accountability. Conventional financial reporting primarily serves shareholders, emphasizing short-term profitability and risk management. In contrast, impact-based reporting under the CSRD integrates ESG considerations into the firm's value-creation narrative. This shift reflects the recognition that long-term corporate resilience depends not only on financial capital but also on human, social, and natural capital.

The CSRD establishes a dual-layered disclosure architecture based on the principle of double materiality, requiring firms to report both:

Financial materiality: how sustainability issues affect the company's financial performance, and

Impact materiality: how the company's activities affect society and the environment.

This dual perspective transforms sustainability reporting from a peripheral voluntary activity into a core component of strategic management. It also redefines corporate transparency, linking firms' external accountability to their internal governance and decision-making processes (Hahn et al., 2015; Schaltegger et al., 2022).

2.2. Theoretical Background of Double Materiality

Although double materiality is often presented as a regulatory innovation, its intellectual roots are grounded in well-established organizational theories. Understanding how firms interpret and implement this concept requires a theoretical framework that connects regulatory expectations with corporate behavior.

Stakeholder Theory: The stakeholder theory states that organizations work in a network of varied stakeholders who exert pressure for transparency and accountability—investors, employees, communities, and government. Meanwhile, Wood's (1991) P-O-R model adopts the tenet that the efficiency of an enterprise depends greatly on how it is managed. Double materiality gives practice to this pluralistic perspective by making the integration of non-financial stakeholders' views in reporting a norm. From this perspective, sustainability disclosure is not simply a due diligence exercise but an act of communication that may serve to engage with stakeholders and negotiate value.

Legitimacy Theory: According to legitimacy theory (Suchman, 1995), organizations desire their actions to be congruent with social standards in order to maintain legitimacy. CSRD disclosures can therefore be looked upon as legitimacy-seeking processes in which companies seek to demonstrate compatibility with the EU's sustainability agenda as a strategy for gaining social and regulatory acceptance. Disclosure of environmental and social impacts increases the perceived legitimacy as well by sending a symbolic message that "we conform to community norms and values, in this case through activities which are beneficial for society" (Deegan, 2002).

Institutional Theory: Institutional theory (DiMaggio and Powell, 1983) gives a macro-level reasoning for the unification of corporate reporting practices. The application of coordinated schemes such as ESRS leads to institutional isomorphism—companies imitate the same

transparency behaviors following coercive (regulatory), normative (professional), and mimetic (imitative) modes. “Double materiality,” then, is a heuristic-as-it-gets for an institutional framework form that enforces homogeneity across sectors but not rigidity against specific applications.

Signaling Perspective: According to signaling theory (Spence, 1973), sustainability reporting acts as a communication signal that indicates credibility, trustworthiness, and risk consciousness to investors and other stakeholders. Those firms that have high-quality, well-displayed CSRD disclosures are sending strong messages regarding strategic antennae and a long-term value focus, whereas lackluster or patchy disclosure can be subject to homage-based interpretations as risk signals or symbolic obedience.

2.3. Integrating Theories into the CSRD Context

Together, these theoretical perspectives elucidate the behavioral dynamics underlying double materiality reporting. Stakeholder and legitimacy theories explain why firms engage in sustainability disclosure. Institutional theory explains how regulatory frameworks produce convergence in disclosure practices. Signaling theory explains how firms differentiate themselves within that convergence through voluntary depth, tone, and assurance mechanisms.

Thus, the theoretical framework positions double materiality as a multi-dimensional construct—simultaneously reflecting compliance (institutional), legitimacy (social), communication (signaling), and accountability (stakeholder) dimensions. This integrated lens not only enriches the conceptual foundation of the study but also guides the empirical analysis that follows, particularly the content analysis of the first 100 CSRD reports.

2.4. Conceptual Model of the Study

Based on the above, this study conceptualizes double materiality as the intersection between, (i) The firm’s external impact on stakeholders (impact materiality), and (ii) The internal significance of sustainability issues for financial performance (financial materiality).

This intersection creates a bidirectional flow of accountability, where regulatory compliance, stakeholder legitimacy, and strategic signaling interact dynamically. We depict the conceptual linkage between the theoretical constructs (i.e., stakeholder, legitimacy, institutional, and signaling mechanisms) to CSRD reporting structure and empirical coding scheme in Figure 1.

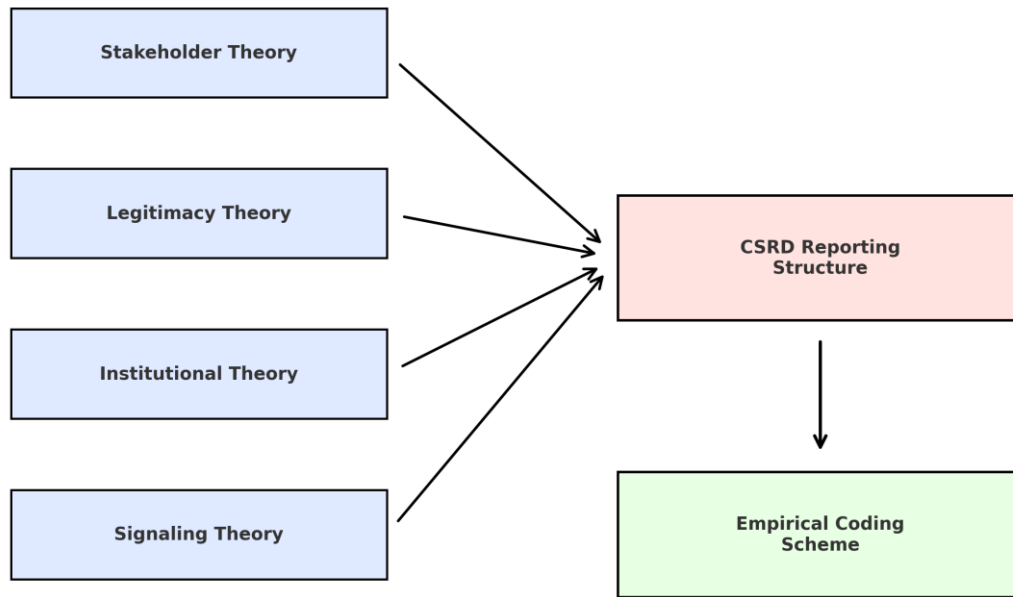


Figure 1. Conceptual Model

3. Related Literature (Table A1)

Research attention to sustainability reporting has surged in the past two decades, resulting in a vast literature on its development, motivations, and implications. Yet, the inclusion of KPIs clearly advances extant literature, which has addressed these issues only partially because of the current changes in regulation enacted through the CSRD and ESRS. To situate our present study within this emergent backdrop, the subsequent literature review distills previous work into three overarching thematic streams; (i) The concepts of and debates around materiality and double materiality, (ii) Empirical data concerning both sustainability reporting practices and standard adoption, and (iii) The evolving importance of assurance, investor confidence, and accountability.

Over the past years, ‘materiality’ and ‘double materiality’ have emerged to become one of the most debated issues in sustainability reporting. Recent studies during the period 2023–2025 reveal that these ideas are not only a techno-rational compliance necessity, but also encode a complex universe made up of corporate credibility, investor beliefs, and regulatory morality. In this context, the literature converges on three main axes of discussion. These are: (i) conceptual debates, (ii) examples of implementation and early adoption, and (iii) investor and stakeholder impacts.

At the conceptual level, Oll et al. (2025) argue that the concept of materiality is based on a fundamental debate and that plurality, rather than conceptual uncertainty, will determine the future of sustainability reporting. Similarly, Aprile et al. (2023) address materiality within the context of systems theory, demonstrating that different interpretations can enrich reporting standards. This literature shows that double materiality is shaped by multiple perspectives rather than a single interpretation.

Dragomir et al. (2025) note that dual materiality applications still contain uncertainties and that stricter regulation and transparency are needed within the CSRD framework. Correa-Mejia et al. (2024) highlight ‘discourse-action’ inconsistencies in the reports of early adopters,

emphasizing that declared double materiality leads to limited change in practice. Szalacha (2024), using the example of Poland, shows that the application of double materiality brings consistency to reporting, but cross-sector comparability remains weak. These findings highlight the gap between regulatory pressure and corporate practices.

Shen et al. (2025), in their empirical study covering 34 countries, found that investors value accountable environmental performance more than mere disclosure. Similarly, Eriandani and Winarno (2024) show that reporting material issues mitigates the negative effects of ESG risks on firm value. Gromis Di Trana et al. (2024) emphasize that stakeholder engagement is cyclically linked to materiality assessments, with cultural and organisational factors shaping this process. This literature demonstrates that double materiality is not merely an internal accounting practice but also a strategic tool in terms of investor confidence and stakeholder engagement.

Tang and Cooper (2025) address materiality in the context of artificial intelligence, drawing attention to the risk of GenAI outputs becoming detached from 'material reality.' This study demonstrates that materiality discussions are being redefined not only along the axes of regulation and implementation but also through the epistemic boundaries of technological developments. This constitutes the innovative and forward-looking dimension of the literature.

The existing literature has addressed the concepts of materiality and double materiality from different angles; however, three key gaps remain apparent; (i) Regulation–implementation gap: There is a discrepancy between what companies declare and what they actually achieve in their reports, (ii) Stakeholder/investor imbalance: The balance between financial materiality and impact materiality remains controversial, (iii) New contexts: Digitalisation and artificial intelligence are opening up new areas of debate that redefine materiality. These gaps enable us to position our study beyond the existing literature.

3.1. Conceptual Debates on Materiality

Materiality in sustainability accounting is a contested issue. Hahn et al. (2015) discuss the challenges surrounding different interpretations of materiality, often regarded as a "cloudy matrix" of thought where several approaches have been criticized. The Chicago School's tradition has greatly influenced the understanding of materiality, emphasizing its importance and the criteria for declaring items immaterial.

During the early stages of sustainability research, highlighted concerns about reporting items crucial to shareholder decisions. They noted the disparities in wealth generation, where some individuals profit while others incur losses, stressing the need for intergenerational accountability (Dragomir et al., 2025).

Initially, materiality discussions centered around financial views, focusing on investor relevance and decision-usefulness. The efforts of GRI and frameworks like Europe's CSRD have broadened materiality to include stakeholder expectations (Schaltegger et al., 2022).

Recent studies, such as those by Oll et al. (2025) and Dragomir et al. (2025), redefine materiality's traditional boundaries, emphasizing its epistemological shifts in sustainability reporting. According to Oll et al. (2025), materiality is an "essentially contested concept," shaped by legitimacy and accountability interpretations. Dragomir et al. (2025) highlight the necessity for stringent methodological guidance to ensure consistent reporting.

Research remains divided between normative interpretations (what double materiality should mean) and operational interpretations (how it is measured and reported). This division underscores the need for integrative frameworks linking regulatory intent with theoretical foundations, a gap addressed by situating research on CSRD implementation within stakeholder, legitimacy, and institutional theory.

3.2. Empirical Evidence on Early Adoption and Reporting Practices

Research on sustainability information disclosure has accelerated with CSRD's introduction. Recent studies examine raw content to identify potential issues and compare practices across companies (Shen et al., 2025). While integration of sustainability frameworks is growing, reporting remains largely compliance-driven. Shen et al. (2025) find that environmental materiality receives more focus, while social and governance aspects are less emphasized. Shen et al. (2025) identify variations in disclosure across countries, indicating that national contexts influence sustainability reporting. Methodological studies employing ESG scores and discourse framing further reveal discrepancies in double materiality interpretations. These studies illustrate a gap between regulatory expectations and corporate practices, highlighting the need for theory-driven analyses like this study.

3.3. Assurance, Investor Trust, and Accountability

Research also explores the credibility of sustainability disclosures. Assurance mechanisms are crucial for transforming sustainability reporting into a reliable governance tool, beyond just public relations. External assurance references can increase investor confidence and mitigate "greenwashing" accusations (Michelon et al., 2019), though assurance practices vary across the EU.

The ESRS framework mandates alignment with the ISSA 5000 standard for assurance, yet academic discourse on its integration with materiality assessments is lacking. This study extends the inquiry by examining whether early CSR adopters reference assurance in their disclosures, how they describe materiality methods, and how these relate to stakeholder communication strategies.

3.4. Methodological Patterns and Research Gap

Explicit patterns in previous studies show reliance on content analyses (Neuendorf, 2017; Krippendorff, 2019), with varied coding methods leading to differing results. Methodological transparency and reliability are often lacking, resulting in descriptive rather than analytical publications.

Identified gaps include; (i) Lack of empirical investigation on corporations' handling of "double materiality" in the CSRD era, (ii) Insufficient understanding of institutional pressures and legitimacy impacts on transparency, (iii) Limited methodological detail in content analysis and assurance studies. This paper addresses these gaps from both a theoretical and practical perspective, aiming to connect regulatory innovation with organizational behavior and sustainability governance.

4. Methodology

4.1. Research Design

The study adopts a qualitative content analysis approach to examine how early CSRD adopters incorporate double materiality principles in their reports. Structural analysis holistically evaluates textual data, identifying patterns, themes, and conceptual relationships (Neuendorf, 2017; Krippendorff, 2019).

Following a theory-driven design combining inductive and deductive reasoning, categories are derived from regulatory frameworks (CSRD, ESRS 1–2), with empirical data emerging from iterative readings. This hybrid approach ensures rigorous analysis and context-specific insights (Schreier, 2022).

4.2. Sampling and Data Collection

The dataset comprises 100 sustainability reports from firms identified as "first adopters" of CSRD between January and July 2024. The reports were selected from the Global Reporting Initiative (GRI) Repository, the European Financial Reporting Advisory Group (EFRAG) Disclosure Register, and official corporate website databases.

Three selection criteria were used: Reports mentioning CSRD and ESRS compliance, availability of full-text English, and sectoral diversity spanning energy, aviation, manufacturing, telecommunications, and more. This sample provides insights into early adoption practices. A full list of companies is available in Table A2.

4.3. Coding Scheme and Analytical Framework

The analysis focused on three core aspects of double materiality:

Table 1. Coding Scheme

Dimension	Definition	Examples of Codes
Financial Materiality	Issues affecting financial performance or value	Revenue impact, cost exposure, investor trust, risk disclosure
Impact Materiality	Environmental or social footprint	Carbon emissions, biodiversity loss, community welfare, labor conditions
Governance Materiality	Linking sustainability plans to oversight and accountability	Board responsibility, ESG committee, assurance disclosure

Reports were manually coded with a codebook tailored to ESRS 1–2 disclosure requirements. Coding involved three phases:

1. Pilot coding (10 reports) to refine categories and definitions;
2. Full coding using NVivo 14;
3. Validation and recoding for consistency.

Emerging themes included legitimacy signaling, institutional isomorphism, and stakeholder responsiveness, aligning with the earlier theoretical framework.

4.4. Reliability and Validity

The established reliability criteria (Lombard et al., 2002; Krippendorff, 2019) were upheld in order to guarantee methodological transparency and replicability.

Inter-coder reliability was established by double-coding 20% of the data. The resulting Krippendorff's α was 0.82, reflecting substantial agreement.

Construct validity: Coding categories had been inductively derived from ESRS frameworks and theoretical building blocks (stakeholder, legitimacy, signaling).

Triangulation: Comparability was achieved by interpretation across regulatory documents, academic literature, and empirical data. Reflexivity was achieved by writing memos and auditing codes throughout the analysis to reduce researcher bias.

4.5. Data Analyzed and Interpreted (Table A3)

After coding procedures, frequency and co-occurrence analyses were used to identify predominant disclosure themes and patterns of cross-sector variation. The analysis took place in three steps:

1. Descriptive map of coverage of disclosure by ESRS subject domains.
2. Cross-industry and firm-size comparisons.
3. Interpretive insight pulling the patterns out of the empirical data to connect these levels of analysis with theories of legitimacy, signaling, and institutional isomorphism.

The focus was not only on what companies disclose, but also how they reason materiality—whether reporting represents a sincere commitment or symbolic cover. Such focus on interpretation is consistent with earlier appeals towards interpretive construction of sustainability reporting beyond pure enumerating descriptions (Hahn and Figge, 2011).

5. Findings and Discussion

5.1. Trend of Disclosure Under CSRD

The review of the initial 100 CSR-driven Sustainable Reports highlights a diverse pattern of adoption according to sectors and size classes. Although all companies formally referred to the CSRD and ESRS frameworks, there were wide differences in the extent and coverage of disclosure.

Around 78% of companies disclosed that they performed a double materiality assessment (DMA), but only 46% shared detailed information on the approach, stakeholder engagement, or priority matrix. This would imply that awareness of compliance is more widespread than the operationalization of double materiality, which is still in an early stage regarding institutional diffusion.

Sectoral differences were also evident. Although energy and manufacturing companies demonstrated more mature integration of impact materiality resulting from established environmental risk frameworks, other service sectors (e.g., finance, aviation, telecom) emphasized governance and relations with stakeholders more strongly. These forms of mimicry

reflect institutional isomorphism, where the organization mimics other firms in its sectoral logic to gain legitimacy (DiMaggio and Powell, 1983).

5.2. ESG Materiality and Other Stories: An Isomorphism Perspective

Cross-sectoral contrasts show that environmental disclosures are the main driver for double materiality considerations, and it is followed by social aspects, as well as governance.

Environmental content, including GHG emissions, energy efficiency, and resource circularity, was present in 91% of reports.

The social inclusions (e.g., diversity, occupational health, impact on the community) are in 63%.

Governance-related disclosures (board oversight, Audit Mechanism) in 52%.

This distribution indicates an evolution from pre-ESG, where we had GRI ESG reporting in the past. For instance, environmental figures have been standardized for a long time. The institutional theory view assists in understanding this harmonization, toward overlapping environmental disclosures, by providing firms with coercive pressures of EU legislation and normative pressures determined in professional assurance standards (Correa-Meija, 2024).

But differences remain in the ways companies describe impact materiality. While MNCs engage in stakeholder mapping and quantitative measures, SMEs use narratives or symbols to talk about compliance. This supports the claim that double materiality is still institutionalized in structure, but not (yet) in practice, as evidenced in earlier stages of diffusion of sustainability standards (Boiral et al., 2021).

5.3. Financial Materiality and Signaling Mechanisms

Unlike impact materiality, the financial materiality in the studied reports was relatively brief. Only one-third of the companies specifically associate environmental or societal risks with financial reporting or key performance indicators. Instead, most companies had general things to say about “sustainability risks may have an impact on future profitability” rather than quantifying it.

The conservative language used here can be considered a type of signal to an external audience and read in a signaling theory framework (Spence, 1973). Companies seek to evidence awareness without showing weakness. However, those with quantified reporting – specifically for the energy and transport sector – experienced a stronger benefit of enhanced credibility and analyst attention presence, supporting the hypothesis that signaling transparency is conducive to stakeholders’ trust building (Michelon et al., 2019).

This observation also contributes to a dichotomy noted by previous literature between substantive and symbolic disclosure (Hahn and Figge, 2011) in the sense that all firms symbolically adopt CSRD language while less materialize this adoption into economically integrated reportage.

5.4. Assurance and Governance: Legitimacy Reinforcement

In only 37% of reviewed reports, explicit reference was made to external assurance audit sources regarding sustainability disclosures. Most of these were planning to perform a lesser level of assurance, while only 6 indicated they would perform reasonable assurance in line with ISSA 5000.

The level of assurance references has a positive relationship with the disclosure of board-level oversight. Companies that set up ESG committees or sustainability governance boards were significantly more likely to publish detailed double materiality assessments and assurance engagements.

Suchman's (1995) legitimacy theory: assurance practices signify conformity with societal and regulatory demands upon which the structure of a social contract is grounded. Additionally, these results connect with stakeholder theory (Freeman, 1984), suggesting that formal assurance acts to boost the trustworthiness of the relationship between firms and stakeholders, including institutional investors and regulators.

5.5. Cross-Theoretical Interpretation

Synthesizing these empirical observations, three theoretical dynamics emerge:

Table 2. Theoretical Dynamics

Theoretical Lens	Empirical Manifestation	Interpretation
Institutional Theory	Convergence in disclosure structures across industries.	Coercive and normative pressures from EU regulation drive harmonization of reporting practices.
Legitimacy Theory	Increased assurance and governance reporting.	Firms seek social and regulatory acceptance by demonstrating compliance credibility.
Signaling Theory	Selective transparency in financial materiality.	Firms use sustainability communication as a strategic signal of responsibility while managing reputational risk.

5.6. Discussion: Towards an Impact-Reporting Framework

The empirical findings show that the CSRD is underway in creating an impact accounting regime. Most organizations display procedural conformity in infusing CSRD language and ESRS sources while trailing behind on putting materiality into action: on strategy, risk technique, and financial reporting. This partial institutionalization might be regarded as an adolescent phase in the life cycle of regulatory diffusion (Hahn et al., 2015). As all of these aspects mature and become more standard, accounting will also evolve to a place where it hopefully converges towards more impact-focused disclosure practices.

From a macro level perspective, three realizations are underscored by the findings; (i) Institutionalization comes before standardization; companies first imitate the compliance as a behavior, only to develop much more mature analytic models. (ii) Disclosures evolve with legitimacy; market and governmental pressures push adoption more than strategic choices to be

sustainable. (iii) Assurance is a credibility bridge: it’s what ties symbolic compliance with the substance of accountability.

Overall, the first wave of CSRD adopters reveals that double materiality is both a technical frame and a social process—a tool through which organizations negotiate legitimacy, make meaning, and signal accountability in an emergent sustainability landscape.

6. Conclusion and Implications

6.1. Theoretical Contributions

This paper adds to the recent scholarly debate on reporting as a double materiality, wherein it is articulated both as a conceptual development and an institutional stage. Although previous work has mostly approached the CSRD from a regulative or descriptive perspective, we draw on stakeholder, legitimacy, institutional, and signaling theories to explain how firms frame, enact, and talk about double materiality in practice.

The results contribute to knowledge in three respects. First, the study shows that reporting convergence happens mainly as a result of institutional isomorphism, which means that coercive and normative pressures, rather than strategic voluntary action-pattern early adopters’ behavior. Secondly, the findings offer empirical evidence to legitimacy theory and show that assurance and governance disclosures act as channels through which firms seek social and regulatory approval. Third, the study enlarges signaling theory, showing how selective transparency in financial materiality constitutes a reputational strategy through which responsibility can be sold and risks earned.

Across the paper, it is therefore argued that double materiality operates as a multi-theoretical hybrid that provides for the capture of regulatory adherence, stakeholder responsibility, and strategic communication. This holistic theoretical focalization effectively contributes to sustainability accounting literature by linking institutional mechanisms and organizational behavior.

6.2. Practical and Policy Implications

From a practical standpoint, the findings highlight that early CSRD adopters have initiated an important shift toward impact-based reporting, but the transition remains incomplete. Firms tend to exhibit procedural compliance-integrating CSRD terminology and structures without fully embedding materiality insights into strategic decision-making. To accelerate substantive adoption, several implications emerge:

For more rapid and meaningful adoption, several implications are revealed. Firstly, for corporate managers: Organizations need to incorporate double materiality in enterprise risk management and strategic planning, where sustainability data not only supports operations but drives financial decisions. Second, for policymakers and regulators: EC and EFRAG should better specify, on a business-by-business basis, the methodologies for materiality and assurance expectation to achieve a certain level of comparability between the reports. Thirdly, for auditors and assurance providers: Preparing strong methodologies under ISSA 5000 will be fundamental to turning sustainability assurance into a meaningful form of validation, rather than a mere symbol

of it, which investors feel they can trust. Fourthly, educators and professional bodies: The inclusion of CSRD-aligned sustainability accounting modules in accounting and auditing curricula will equip accountants for the uniform application of ESRS standards.

From the macro perspective, the findings indicate that firm regulators and assurance actors need to collaborate for integrated CSRD so as to establish a balanced ecosystem conducive to enhancing transparency, comparability, and accountability.

6.3. Directions for Future Research

As one of the initial empirical analyses of early CSRD adopters, this study is not without limitations and guideposts for further research.

Big Sample and Longitudinal: In the future, from the dataset extension to the 100th firm onwards, to count on late adopter firms and do longitudinal comparison of discloser quality variation in time.

Quantitative Pathways: It would be possible to add content analysis findings into financial performance measures or ESG ratings to see whether double materiality disclosures correspond with actual business results.

The Cross-Country and Cultural Dimension: Comparative analysis among EU member states could investigate how institutional context, legal tradition, and societal expectations condition the reception of double materiality.

The Use of Assurance and Credibility Perception: Future studies may explore how the different depth of assurance (restricted vs. reasonable) is related to stakeholders' perceived trustworthiness.

Artificial Intelligence and Automated Reporting: As corporate users of AI-based ESG analytics grow, automation's implications for CSRD transparency in terms of its quality, accuracy, and accountability may warrant further investigation.

By following these paths, researchers will be able to further expand our knowledge of sustainability reporting as a developing social-technical system—where regulation, corporate practice, and stakeholder expectation are dynamically entangled.

6.4. Final Evaluation

The adoption of the CSRD is a game-changer for corporate responsibility as it denotes a shift towards impact materiality over financial materiality and from voluntary to mandatory disclosure regarding sustainability-related information.

But, as this research shows, regulation alone does not ensure that changes take root. The essence of the challenge is to convert compliance from a ritual into meaningful corporate change - where obsessed disclosure takes on multiple roles: learning, governance, and sustainable value creation.

In short, the principle of dual materiality, deeply embedded in corporate strategy, has the potential to transform how companies view responsibility, risk, and resilience. The shift to impact-based reporting heralds not only a new regulatory era but also a different approach to

accountability, where transparency is no longer divorced from trust and sustainability is paramount to corporate success.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest

There are no potential conflicts of interest in this study.

Ethical Considerations

All data used in this study are publicly available. No confidential or proprietary information was accessed. Citations, coding decisions, and interpretations adhere to ethical research standards as outlined in the European Code of Conduct for Research Integrity (ALLEA, 2023).

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APPENDIX**Table A1. Related Literature**

Authors	Article Title	Methodology	Revised Findings	Category Synthesis
Pozzoli et al. (2024)	Does financial materiality judgement matter in reporting intellectual capital? A systematic literature review and future research trends	Systematic literature review	The concept of financial materiality has been addressed in intellectual capital reporting using different approaches, and four research trends have been identified in which both quantitative and qualitative thresholds are discussed.	Studies falling into this category consist of publications that do not directly link materiality to theoretical or applied discussions, but offer indirect contributions to the topic.
Aprile et al. (2023)	Enhancing the materiality principle in integrated reporting by adopting the General Systems Theory	Content analysis	The principle of materiality has been reinterpreted within the framework of General Systems Theory, proposing a more functional understanding for managers and regulators.	Studies falling into this category discuss the theoretical foundations of the concepts of materiality and dual materiality. In particular, it emphasizes that materiality is based on conceptual pluralism and is enriched by different theoretical frameworks (e.g., systems theory). The literature suggests that pluralism, rather than a single, uniform understanding of materiality, will shape the future of sustainability reporting.
Oll et al. (2025)	The concept of materiality in sustainability reporting: from essential contestation to research opportunities	Systematic review	It demonstrates that the concept of materiality stems not from uncertainty but from substantive debate, and therefore conceptual pluralism will shape the future of sustainable reporting.	Studies falling into this category discuss the theoretical foundations of the concepts of materiality and dual materiality. In particular, it emphasizes that materiality is based on conceptual pluralism and is enriched by different theoretical frameworks (e.g., systems theory). The literature suggests that pluralism, rather than a uniform understanding of materiality, will shape the future of sustainability reporting.
Belidan and Baghdad (2024)	Navigating materiality in sustainability reporting: A scoping review of single and double materiality approaches	Content analysis	Studies on single and double materiality approaches in the literature are still limited; this points to new areas of research.	This group focuses on how dual materiality is implemented in practice. Reports in early adopter companies often appear to contain gaps between rhetoric and action. However, in some cases, the implementation of dual materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Beyne and Moratis (2025)	A material world: how can materiality assessments be used to define organizational sustainability priorities, while taking into account the United Nations' SDGs?	Survey research	Most companies struggle to integrate SDGs into materiality analysis, with information and methodology gaps limiting this process.	This group focuses on how dual materiality is implemented in practice. Reports in early adopter companies often appear to contain gaps between rhetoric and action. However, in some cases, the implementation of dual materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Correa-Mejia et al. (2024)	Analysis of double materiality in early adopters. Are companies walking the talk?	Content analysis	Although double materiality statements have been made by early adopters, it has been found that material topics in reports have changed only to a limited extent.	This group focuses on how dual materiality is implemented in practice. Reports in early adopter companies often appear to contain gaps between rhetoric and action. However, in some cases, the implementation of dual materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
De Cristofaro and Gulluscio (2024)	In Search of Double Materiality in Non-Financial Reports: First Empirical Evidence	Content analysis	Initial empirical evidence points to limited traces of double materiality in non-European companies and more pronounced traces in Europe.	This group focuses on how dual materiality is implemented in practice. In early-adopter companies, reports often contain gaps between rhetoric and action. However, in some cases, the implementation of double materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Dragomir et al. (2025)	Double Materiality Disclosure as an Emerging Practice: The Assessment Process, Impacts, Risks, and Opportunities	Content analysis	Clearer, more detailed guidance and stricter regulations under the CSRD are needed for the effective implementation of the double materiality concept.	This group focuses on how double materiality is implemented in practice. In early-adopter companies, reports often contain gaps between rhetoric and action. However, in some cases, the implementation of double materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Lee (2024)	Double Materiality Assessment and ESG Management: A Comparative Study of Global Steel Corporations	Content analysis	A comparative analysis of steel companies shows progress in ESG integration, but differences persist.	This group focuses on how double materiality is implemented in practice. In early-adopter companies, reports often contain gaps between rhetoric and action. However, in some cases, the implementation of double materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Nielsen (2024)	ESG Reporting and Metrics: From Double Materiality to Key Performance Indicators	Content analysis	Direct links have been established between double materiality and performance indicators in ESG reporting.	This group focuses on how double materiality is implemented in practice. In early-adopter companies, reports often contain gaps between rhetoric and action. However, in some cases, the implementation of double materiality has increased reporting consistency. The findings point to a regulation-implementation gap.

Table A1. Continued

Szalacha (2024)	Double materiality implementation and its impact on sustainability reporting: Findings from Polish early adopter reports	Content analysis	Early adopters in Poland have increased reporting consistency through materiality practices, but cross-sector comparability remains limited.	This group focuses on how dual materiality is implemented in practice. Reports in early-adopting companies often contain gaps between rhetoric and action. However, in some cases, the implementation of dual materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Tan and Dipendra (2024)	Tensions between Materiality Assessments and Stakeholder Engagements in Thai Corporate Sustainability Leaders	Content analysis	Materiality assessments are generally conducted more systematically than stakeholder engagement, suggesting that stakeholder-focused standards may be superficially implemented in practice.	This group focuses on how dual materiality is implemented in practice. Reports in early-adopting companies often contain gaps between rhetoric and action. However, in some cases, the implementation of dual materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Di Trana et al. (2024)	The interplay between stakeholder engagement and sustainability materiality assessment: a circular perspective	Qualitative research	There is a cyclical relationship between stakeholder engagement and materiality assessments; multidisciplinary and cultural factors shape this process.	This group focuses on how dual materiality is implemented in practice. Reports in early-adopting companies often contain gaps between rhetoric and action. However, in some cases, the implementation of dual materiality has increased reporting consistency. The findings point to a regulation-implementation gap.
Eriandani and Winarno (2024)	ESG Risk and Firm Value: The Role of Materiality in Sustainability Reporting	Content analysis	Materiality reporting can play a role in mitigating the negative impact of ESG risks on firm value.	This category addresses the perspectives of investors and stakeholders on the concept of materiality. Empirical findings suggest that investors should not only report but also perform accountably.
Festa et al. (2024)	The Unintended Consequences of Audit Materiality Disclosures on Whistleblowing Intentions	Content analysis	Disclosure of materiality thresholds can reduce investors' whistleblowing intentions.	This category addresses investors' and stakeholders' perspectives on the concept of materiality. Empirical findings indicate that investors value accountable performance, not just disclosure. Furthermore, the interaction between stakeholder engagement and materiality assessments is shaped by factors such as corporate culture and multidisciplinary approach.
Festa et al. (2024)	Auditor Materiality Disclosures and Investor Trust: How to Address Conditional Risks of Disclosure Mandates	Content analysis	Quantitative materiality disclosures can be misleading when investor concerns about earnings management increase.	This category addresses investors' and stakeholders' perspectives on the concept of materiality. Empirical findings indicate that investors value accountable performance, not just disclosure. Furthermore, the interaction between stakeholder engagement and materiality assessments is shaped by factors such as corporate culture and multidisciplinary approach.
Schiehl and Kolahgar (2025)	Common ownership and investor-focused disclosure: Evidence from ESG financial materiality	Quantitative analysis	This demonstrates that shared ownership influences companies' financial materiality-focused disclosures and shapes investor expectations.	This category addresses investors' and stakeholders' perspectives on the concept of materiality. Empirical findings indicate that investors value accountable performance, not just disclosure. Furthermore, the interaction between stakeholder engagement and materiality assessments is shaped by factors such as corporate culture and multidisciplinary approach.
Shen et al. (2025)	Does environmental materiality matter to corporate financial performance: Evidence from 34 countries	Multilevel regression model	Investors reward accountable environmental performance over disclosures based solely on statements, demonstrating that environmental materiality is directly related to financial performance.	This category addresses investors' and stakeholders' perspectives on the concept of materiality. Empirical findings indicate that investors value accountable performance, not just disclosure. Furthermore, the interaction between stakeholder engagement and materiality assessments is shaped by factors such as corporate culture and multidisciplinary approach.
Xie et al. (2023)	Do investors incorporate financial materiality? Remapping the environmental information in corporate sustainability reporting	Content analysis	The integration of financial materiality within the SASB framework can enable more effective reporting of environmental risks.	This category addresses investors' and stakeholders' perspectives on the concept of materiality. Empirical findings indicate that investors value accountable performance, not just disclosure. Furthermore, the interaction between stakeholder engagement and materiality assessments is shaped by factors such as corporate culture and multidisciplinary approach.
Albuquerque et al. (2024)	What material topics by ESG dimensions can be found within the materiality matrix from the European entities' sustainability reports?	Content analysis	Materiality issues have been identified in European companies' reports based on ESG dimensions, and these issues have provided guidance for regulators, investors, and practitioners. Materiality has been re-discussed in a philosophically aesthetic context.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative future-oriented discussion area in the literature.

Table A1. Continued

Ciavatta (2024)	Hegel's Aesthetics of Materiality	Conceptual	Materiality has been revisited in a philosophically aesthetic context.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative future-oriented discussion area in the literature.
Huang et al. (2024)	The Economic Consequences of Heightened Materiality Uncertainty: An Auditing Perspective	Content analysis	Materiality disputes in companies examined by inexperienced auditors have led to more auditor turnover.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative, future-oriented discussion area in the literature.
Kuu-Park et al. (2024)	Materiality in community energy innovation: A systematic literature review of hands-on material engagement in energy transition	Systematic literature review	In community energy innovation, materiality has been examined in multidisciplinary contexts, and different types of networks have emerged.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative, future-oriented discussion area in the literature.
Miettinen (2024)	Are materiality determination practices evolving in the wake of increasing legislation on sustainability reporting? Findings from EU pharmaceutical companies' reports	Content analysis	In the European pharmaceutical sector, materiality has evolved from NFRD to CSRD, but inconsistencies in definition and reporting persist.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative, future-oriented discussion area in the literature.
Setia et al. (2024)	Shifting perspectives: unveiling the double nature of sustainability materiality in integrated reports	Content analysis	The practical application of double materiality can lead to reporting results that are inconsistent with theoretical expectations.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative, future-oriented discussion area in the literature.
Tang and Cooper (2025)	The Role of Materiality in an Era of Generative Artificial Intelligence	Conceptual (GenAI)	In the context of artificial intelligence, materiality demonstrates the need to connect information to material reality, as opposed to decontextualized outputs.	This group consists of studies that address materiality in new contexts. Artificial intelligence, digitalization, and aesthetic approaches demonstrate that materiality transcends classical reporting frameworks. This opens up an innovative, future-oriented discussion area in the literature.

Table A2. Companies Comprising the Sample

	Company	Country	Report Period
1	Archer Limited	NO (registered BMU/operations NO)	2022-2024
2	Cenergy Holdings SA	BE (registered) / GR operations)	2022-2024
3	Energie Beheer Nederland B.V.	NL	2022-2024
4	Eni SpA	IT	2022-2024
5	Equinor ASA	NO (EEA)	2022-2024
6	Galp Energia, SGPS, S.A.	PT	2022-2024
7	HELLENiQ ENERGY Holdings S.A.	GR	2022-2024
8	Jordanes ASA	NO (EEA)	2022-2024
9	KID ASA	NO (EEA)	2022-2024
10	LPP S.A.	PL	2022-2024
11	Neste Oyj	FI	2022-2024
12	Österreichische Mineralölverwaltung AG (OMV)	AT	2022-2024
13	PetroNor E&P ASA	NO (EEA)	2022-2024
14	Repsol S.A.	ES	2022-2024
15	Shell PLC	UK (listed EU)	2022-2024
16	TotalEnergies SE	FR	2022-2024

Table A3. Findings

Company	Double Materiality Disclosure	IRO Clarity	ESRS/Taxonomy Link	Impact Materiality Themes	Assurance	Overall Evaluation
Archer Limited	Yes. The ESRS 2 IRO 1 process is used as a reference in the audit.	Yes. IRO reported under IRO 1	IRO 1 presented in conjunction with the EU Taxonomy	Yes. Climate, security, and ethics in energy services	Yes. PwC Limited Assurance (ISAE 3000)	Strong compliance with ESRS IRO 1
Cenergy Holdings SA	Yes. A four-step method is being followed.	Yes. Thresholds/stakeholder inputs are defined	Presented with ESRS-referenced content and index	Yes. Climate and governance in cable/energy infrastructure	Yes. Limited Assurance (ISAE 3000)	Structured process with stakeholder input
Energie Beheer Nederland B.V.	Yes. The governance risk basis for transitioning from ESRS 2 to IRO 1 is in place.	Partially. Method/framework exists; maturation is planned	ESRS 2 linked to IRO 1 and the EU Taxonomy	Yes. Energy transition focus	No explicit assurance findings identified	Framework exists, but assurance gap
Eni SpA	Yes. Sustainability Statement designed in accordance with ESRS	Yes. Compatible with IRO + EU Taxonomy	Separate Sustainability Statement presented	Yes. Energy transition and financial impacts	Yes. Limited Assurance (ISAE 3000)	High alignment with ESRS + assurance
Equinor ASA	Yes. The IRO 1 process has been verified through the audit process.	Yes. IRO is under ESRS 2 IRO 1	Sustainability Statement and Taxonomy presented	Yes. Core energy sector issues	Yes. EY Limited Assurance (ISAE 3000)	Verified IRO process, strong assurance
Galp Energia, SGPS, S.A.	Yes. The methodology has been explained in detail.	Yes. The two dimensions are considered together.	Structure according to ESRS + KPIs Sustainability Statement + Taxonomy	Yes. Energy transition and occupational safety	Yes. Independent Limited Assurance	Detailed methodology, independent assurance
HELLENiQ ENERGY Holdings S.A.	Yes. The process is explained according to IRO 1.	Yes. IROs are included in IRO 1.	Sustainability Statement + Taksonomi	Yes. Refinery/marketing focus	Yes. EY Hellas Limited Assurance	Clear process and EY assurance
Jordanes ASA	Yes. Scored based on seriousness/probability/stakeholder.	Yes. Impact + risk/opportunity are framed together.	Matrix/mapping with ESRS codes	Yes. Food and agriculture supply chain focus	No explicit assurance findings	Good coverage, lacks assurance
KID ASA	Yes. There is an explanation of Impact, Risk & Opportunity.	Yes. Material/Note material distinction is clear.	ESRS data point/index + Taxonomy	Yes. Retail – human rights/ethics/supply chain	Yes. PwC Limited Assurance	Clear materiality distinction + PwC assurance
LPP S.A.	Yes. There is a process according to IRO 1 and indexing according to ESRS.	Yes.	Table linked to ESRS + policy established	Yes. Circularity/human rights	Yes. Grant Thornton Limited Assurance	Circularity focus + assurance
TotalEnergies SE	Yes. Process under ESRS 2 IRO 1/2	Yes. IRO presentation is available under IRO 1/2.	ESRS sections + incorporation by reference	Yes. Climate, pollution, circularity, Taxonomy	Auditor Certification Reports (Limited)	Strong CSRD alignment + auditor certification
Shell PLC	Yes. The double materiality process is included in the report and the auditor's report.	Yes. Material IRO coverage confirmation is available.	Sustainability Statements (ESRS 2, E1–E5, S, G)	Yes. Oil and gas core issues	Limited Assurance (Independent Auditor)	High transparency, independent assurance
Repsol S.A.	Yes. The materiality assessment / double materiality section is available.	Yes. IRO presentation is available under ESRS.	Appendix V and ESRS indexes	Yes. Climate, pollution, water, circularity	Yes. PwC Limited Assurance	Comprehensive coverage, PwC assurance
Österreichische Mineralölverwaltung AG (OMV)	Yes. Sustainability Statement ESRS; auditor Reference to double materiality present	Yes. The auditor evaluates the information determined by the EO.	General/Environmental/Social/Governance + Assurance	Yes. E1–E5 + Taxonomy focus	Yes. KPMG Limited Assurance	Strong assurance with KPMG
Neste Oyj	Yes. Sustainability statement; ESRS 2 General Disclosures available	Yes. E/S/G and Taxonomy are explained.	Within the YKB report; complies with Article 8	Yes. Sector priorities such as E1, E2, E4, E5, etc.	Yes. KPMG Limited Assurance	Detailed disclosures with KPMG
PetroNor E&P ASA	Partially. 2023; ESRS referenced; comprehensive dual materiality plan available in 2024	Partially. Materiality is explained; structured expansion plan.	ESRS index/core policies within the ESG report	Yes. Climate/environmental policies; targets by 2024	No external assurance (2023)	Partial implementation, no assurance in 2023

GLOBAL CLIMATE POLICY UNCERTAINTY AND STOCK RETURNS: EMPIRICAL EVIDENCE FROM BIST SECTORAL INDICES

Küresel İklim Politikası Belirsizlięi ve Pay Getirileri: BIST Sektör Endekslerinden Kanıtlar

Mehmetcan SUYADAL *

Abstract

This study examines the impact of Global Climate Policy Uncertainty (GCPU) on stock market returns in Türkiye at the sectoral level. To this end, the study employs the weekly GCPU Index proposed by Ma et al. (2024) and data for the Borsa Istanbul stock indices covering the period 2000–2023. Quantile regression results reveal not only the extent to which sectors are affected by the global index, but also how climate policy uncertainty influences returns across different market conditions. GCPU exerts a positive and significant effect on energy-intensive electricity sector shares across most market states, whereas the same results emerge in other sectors under different market states. In technology shares, GCPU generates positive effects in lower quantiles (bearish market conditions), while in the chemical, financial, and industrial sectors, such effects emerge in higher quantiles (bullish market conditions). On the other hand, positive and significant relationships are found in the basic metal sector at the top quantile, while similar effects are seen for the services sector at the lowest quantile and middle quantiles. Overall, the results are expected to provide valuable insights for global and local climate-related regulators as well as investors and researchers.

Keywords:

Global Climate
Policy Uncertainty,
Stock Markets,
Quantile Regression.

JEL Codes: D53,
G11, Q54.

Öz

Bu çalışma küresel iklim politikası belirsizliğinin pay piyasası getirilerine etkisini Türkiye’deki sektörler özelinde incelemektedir. Bu kapsamda iklim politikası belirsizliğini temsilen Ma vd. (2024) tarafından önerilen küresel endeks ve Borsa İstanbul pay endekslerine ilişkin 2000-2023 yıllarını kapsayan haftalık veriler kullanılmıştır. Kantil regresyon sonuçları, sektörlerin küresel endeksten etkilenme derecelerini ortaya koymakla beraber, farklı piyasa durumlarında iklim politikası belirsizliklerinin etkilerini de ortaya çıkarmıştır. Çoęu piyasa koşulu için küresel iklim politikası belirsizliği enerji payları yoğun elektrik sektöründe pozitif ve anlamlı bir etki yaratırken, diğer sektörlerde aynı etkiler farklı piyasa koşullarında ortaya çıkmaktadır. Küresel iklim politikası belirsizliği, teknoloji sektörü paylarında düşük kantillerde (ayı piyasa koşullarında) pozitif etkiler yaratırken, kimya, mali ve sınai sektörde bu etkiler yüksek kantillerde (boęa piyasa koşullarında) görölmektedir. Öte yandan Ana Metal sektöründe en üst kantilde pozitif ve anlamlı ilişkiler bulunurken, benzer etkiler hizmet sektörü için en alt ve orta kantillerde görölmüştür. İlgili sonuçların, küresel ve yerel düzeyde iklim politikalarını yürüten düzenleyicilere, yatırımcılara ve arařtırmacılara faydalı olması beklenmektedir.

Anahtar Kelimeler:

Küresel İklim
Politikası Belirsizlięi,
Pay Piyasaları,
Kantil Regresyon.

JEL Kodları: D53,
G11, Q54.

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1. Introduction

Global momentum toward sustainability has encouraged investors to integrate climate risk into their decision-making and to seek opportunities in green-oriented industries. Especially in the past decade, governments, international organizations, and financial institutions have intensified their efforts to mitigate climate change through a range of regulatory frameworks and market-based instruments. For instance, carbon pricing mechanisms, renewable energy subsidies, emission trading systems, and green financial products have become increasingly widespread and supportive of sustainable investment strategies (Ilhan et al., 2021; Huang et al., 2021; Tedeschi et al., 2024). Although there are many regulations to support a low-carbon transition, rising CPU (Climate Policy Uncertainty) at the global scale poses a considerable obstacle to achieving this goal.

CPU refers to the degree of ambiguity regarding future climate-related actions, regulations, and agreements that can shape investment decisions at both individual and corporate levels. Unexpected shifts in regulations, such as delays in climate legislation, inconsistent policy commitments, or changes in subsidy programs, may weaken investor confidence in green projects and hinder renewable energy initiatives planned to meet international climate goals. Moreover, the CPU may negatively affect economic growth, employment, the adoption of renewable energy, agricultural losses, and public health outcomes. For investors, CPU may also influence financial decisions because of creates climate-related risks that are important for portfolio setup and asset choice between risky and resilient assets. Therefore, abrupt climate policy changes can pose significant risks that influence the pricing of stocks and other financial instruments (Fan et al., 2017; Cepni et al., 2022).

From this view, the study explores the impact of GCPU (Global Climate Policy Uncertainty) on the BIST stock returns using weekly data covering from 2000 to 2023, particularly by analyzing its effects across different sectors. This approach allows us to understand the effects of climate risks in terms of return behaviors of sectors. Current literature indicates that there are only a few studies on Turkish stock markets about the effects of CPU (Irani et al., 2022; Ilgın, 2024; Özkan, 2024). Accordingly, this paper contributes by addressing this gap, with a specific focus on sectoral variations in Borsa Istanbul (BIST). Although the CPU index has been calculated for many developed and emerging markets, there is no CPU index exists for Türkiye. To handle this limitation, this paper utilizes the Global CPU Index (GCPU), proposed by Ma et al. (2024). Furthermore, using a quantile regression (QR) approach, this study further investigates the impact of GCPU on sectoral returns under different market states (bearish, neutral, and bullish).

This paper provides evidence for the existing literature in the following important ways. First, it focuses on the Turkish stock market, a context that has been rarely examined in prior research, thereby addressing a significant gap in the literature. Second, the study investigates the heterogeneous effects of the GCPU on sectoral stock returns in Borsa Istanbul, offering disaggregated insights at the sectoral level. Third, by employing a quantile regression (QR) analysis, the paper uncovers how the impact of GCPU varies under different market conditions, thus providing both empirical and methodological contributions to the current literature.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on CPU. Section 3 introduces the weekly dataset and outlines the empirical methodology. Section 4 presents the empirical findings. Section 5 concludes the paper.

2. Literature

In this part, the study classifies the research on the influences of Climate Policy Uncertainty according to policy, institutional, and stock market transmission channels. Since sustainability and climate-related risks represent a relatively new paradigm in academic studies, the literature on the link between CPU and stock market performance remains limited. Studies have primarily focused on the measurement of CPU and its components. For example, in a well-known study, Gavriilidis (2021) developed a measure of climate policy uncertainty via textual analysis of news related to climate policies in the United States media. This index contains major developments like new emission legislation, global climate regulations, policy declarations from authorities, and other prominent issues about climate policy. Similarly, Faccini et al. (2023) classified climate-related reports using textual analysis named Latent Dirichlet Allocation (LDA). They found that U.S. stock prices are mostly driven by risks that generated government policies about climate change. In line with these studies, a growing body of research has been conducted to construct CPU indices for various economies, reflecting local regulations and climate commitments (Berestycki et al., 2022; Ma et al., 2023; Lin and Zhao, 2023; Chen et al., 2024). These critical innovations allow researchers to observe shifts in policy uncertainty over time and to analyze market reactions based on climate-related developments. Moreover, the progress of CPU measures also contributes to empirical financial studies that are interested in the effects of climate-related policy shocks on firm-level decisions, stock market reaction, asset pricing, or risk evaluation.

One strand of the common literature includes the studies that investigate the macroeconomic consequences of CPU. For instance, Li and Su (2022) investigated the impact of China's Climate Policy Uncertainty (CCPU) on macroeconomic conditions using a Vector Autoregression (VAR) model with time-varying parameters. Their results indicate that CCPU negatively affects various macroeconomic indicators such as Total Investment Volume (TIV), Industrial Production Index (IPI), and Purchasing Managers' Index (PMI) over the medium and long horizons. Doğan (2023) documented a positive relationship between CPU and the Consumer Price Index in the U.S. from the data covering the period from 1990 to 2021. In a similar manner, Çelik and Doğan (2024), applying the ARDL bounds test, found a positive and significant relationship between economic growth and CPU. Moreover, they emphasized that the total workforce, foreign direct investment, and financial development also exert a significant influence on U.S. economic growth. Apergis et al. (2023) studied how CPU affects tourism economics. They use CPU index and U.S. air-travel data from different regions and find that the CPU is a factor of aviation demand to all regions. A research on global food price volatility, Eissa et al. (2025), focused on the time-varying effects of CPU. They found that the CPU is the key factor in the global food price volatility.

Another strand of the literature, particularly over the past decade, has focused on the climate policy-related risks from an institutional perspective. For example, Lian et al. (2025) investigate the effects of CPU on banks' loan loss provisions. Utilizing data of 63 commercial banks in China, they found that CPU significantly increases banks' loan loss provisions. Other studies on CPU, Fan et al. (2024) found that CPU negatively affects bank value, while Liu et al. (2025) and Tran (2025) reported that CPU influences the earnings management of firms. In another study, Ayed et al. (2024) examined the corporate dividend policy considering CPU and found that dividend payments increase in times of heightened CPU. Similarly, at times of heightened CPU, firms tend to reduce their investment levels (Huang and Sun, 2024), and CPU

has negative effects on firm value (Azimli, 2023). Ren et al. (2022), in a study that relies on a comprehensive data set, examine the link between CPU and Total Factor Productivity (TFP) using the data of 2605 Chinese companies operating in mining, manufacturing, energy production, and supply industries. Empirical evidence from panel regression analysis shows that the CPU has a significantly negative effect on firms' TFP. Several studies have investigated CPU effects on firm performance through the asset pricing mechanism. For instance, Treepongkaruna et al. (2023) provide evidence that uncertainty-averse investors are willing to pay a premium for stocks that are more sensitive to climate policy uncertainty, resulting in lower expected returns. On the other hand, Huang et al. (2025) examine the cross-sectional link between CPU and expected performance of the Chinese A-share equities manufacturing sector and find that firms with lower CPU betas tend to generate higher annualized returns compared to high-beta firms. Both studies consistently point out that CPU is a priced factor in financial markets.

A large portion of the common literature focuses on the link between CPU and stock market dynamics. These studies are generally conducted on Chinese and U.S. stock markets, as these two countries are the largest carbon emitters globally and play a central role in shaping international climate policy. For instance, in the U.S., even a single policy proclamation or political signal can have an immediate impact on market expectations. In light of this, a comparative study conducted by Xu et al. (2023) to detect how Climate Policy Uncertainty (CPU) affects stock market behavior, focusing on its nonlinear and lagged impacts on returns, volatility, cross-market correlations, and tail dependence in China and the United States. Empirical findings show that the growth of China's CPU index closely mirrors that of the U.S., and the effects of CPU on stock markets differ significantly between the two countries. Specifically, high CPU in China reduces current returns and generates additional volatility, while in the U.S., it reduces returns in the short run but increases them over the long term. Moreover, the CPU increases volatility and strengthens cross-market dependence between the two countries' stock markets. Chen and Wang (2025) analyzed the linkage between CPU and China's stocks using a multilayer network approach. They found that (1) crises increase risk spillovers, (2) network layers respond asynchronously during turmoil, and (3) sectors like industrials and IT often transmit risk, while CPU and financials tend to absorb it. In another study, Chen et al. (2023) investigated the spillover effects of CPU on Chinese stock volatility using the GARCH-MIDAS approach and high-frequency data. Empirical results emphasized that the CPU has a strong effect on stock price volatility in China. Similar results were also observed by Lasisi et al. (2024). They concluded that stock market volatility significantly responds to CPU in the U.S. and U.K. stock markets, while Di Tommaso et al. (2024) reported that CPU has a negative impact on overall stock market indicators such as equity prices and FTSE implied volatility index. Özkan (2024) aimed to detect causal links between CPU and the BIST Food & Beverage Index (XGIDA) using monthly data spanning from 1997 to 2023. Results show that there is a one-way causal link between CPU and the BIST Food & Beverage Index. In a similar study, Pijourlet (2024) finds that CPU has significant effects on sectoral returns using monthly data for ten U.S. industries.

In the literature, studies on financial markets have not only focused on traditional stock markets, but also explored the influence of CPU on fossil and renewable-related asset channels. Among the studies, Tedeschi et al. (2024) analyzed the time-varying effects of CPU on stock market and clean energy indices using a Bayesian TVP-VAR model. They find that financial indices are significantly affected by CPU shocks. Clean energy stocks exhibit positive returns, while those on traditional energy stocks decrease in response to heightened climate risk. Empirical

results also indicate that COVID-19 represents a significant structural break in CPU dynamics. Similarly, Ren et al. (2023), using monthly data and time-varying causality tests, examined the effect of CPU on traditional and green market indices. They utilized crude oil, UK natural gas, and Rotterdam coal data to represent traditional assets, while S&P Global Clean Energy Index, S&P Green Bond Index, and ECX EUA carbon prices were employed to represent green assets. Results imply that there is a significant dynamic causal link between CPU and each series, with these relationships strengthening during periods of major climate actions. Siddique et al. (2023) investigated the influence of CPU on fossil, renewable, and low-carbon energy markets using the monthly data on fossil-based energy commodity futures and renewable energy instruments. Their findings reveal that CPU exerts a considerable inverse effect on most fossil energy futures returns, while renewable and low-carbon assets are affected positively. Iqbal et al. (2024) studied asymmetric effects of the daily Chinese CPU on the various energy-related assets such as Carbon emission allowance prices (CEA), clean energy stock index (CN), environmental, social, and governance (ESG) stock index, and gas oil stock index (GAS) using the NARDL framework. The main results of the model illustrated that a higher Chinese CPU reduces CEA prices, while no significant effect is found on CN and GAS stock prices. In contrast, Chinese CPU causes an increase in ESG stock prices in the long term.

There are also studies in the literature examining whether CPU has a predictive power for future returns or volatility of various asset classes. For instance, He and Zhang (2022) examined the predictive role of CPU for share returns in the crude oil sector. Their findings indicate that CPU is a predictor of future stock returns. Furthermore, based on in-sample and out-of-sample results, CPU proves to be more efficient in forecasting the future stock returns of the oil industry compared to other uncertainty indicators or oil industry-specific factors. In a similar study on forecasting, Lv and Li (2023) tested the predictive power of CPU on Chinese sectoral stock returns volatility using data from various sector indices between 2009 and 2022. Their results show that CPU has strong predictive ability for volatility dynamics of different sectors such as energy, materials, industrials, consumer discretionary, health care and utility. They also noted that during low volatility periods, the CPU becomes a more effective factor for predicting sectoral volatility. Ghani et al. (2024) also reveal that the CPU can predict U.S. stock market volatility, while Liu et al. (2023) found that the CPU has predictive ability for future commodities. Another study conducted by Liang et al. (2022). They tested the forecasting performance of CPU and eight other uncertainty indices in explaining the long-term volatility of the World Renewable Energy Index. Their results prove that the CPU index is a more efficient tool compared to other uncertainty measures for predicting renewable energy index volatility. Lastly, Ding et al. (2025) revealed that CPU predicts cryptocurrency volatilities with superior forecasting performance.

This review highlights the current literature on climate policy uncertainty. Although there are studies focusing on the effects of CPU on stock markets from a sectoral perspective (Lv and Li, 2023; Pijourlet, 2024; Özkan, 2024), the evidence for the Turkish market remains extremely limited. To date, no study has addressed the effects of CPU on BIST stock returns on a sectoral basis. Therefore, this study will fill the gap in the literature by observing the effects of global climate-related activities on Turkish sectoral returns. These approaches also contribute to investment decisions or portfolio allocation amid climate policy risks.

3. Data and Methodological Design

This study employs the weekly form of the GCPU index developed by Ma et al. (2024), in addition to BIST sectoral stock market data spanning from 2000 to 2023. Although many countries have their own Climate Policy Uncertainty indices, there is no such index that exists for Türkiye. Given this shortcoming, the paper utilizes the GCPU to analyze the effects of climate-related risks on different sectors of the Turkish stock market. The construction of the GCPU index follows the methodology proposed by Baker et al. (2016) and U.S. U.S.-based keyword framework of Gavriilidis (2021).

As emphasized by Ma et al. (2024), building a vocabulary for GCPU poses challenges due to linguistic diversity, as most searches are conducted in the local language of each newspaper. To address this, Ma et al. (2024) incorporate climate policy reports from the Intergovernmental Panel on Climate Change (IPCC) and national environmental agencies, drawing inspiration. Following Engle et al. (2020), they expand the vocabulary and ensure contextual relevance across countries. They also consult with native experts in climate policy to determine related keywords for different countries. Following these steps, they designed the final GCPU.

In order to analyze the effects of weekly GCPU on stock markets, the study adopts a quantile regression (QR) approach. First, QR helps to provide robust results by cutting back systematic errors often observed in traditional regression approaches, particularly during market downturns. Second, instead of relying on general market states, QR allows us comparable insights into the link between climate risk and financial markets. Therefore, the study includes all sectors that can be consistently matched with weekly GCPU values over the common sample period (2000–2023) to ensure synchronized and comparable observations. BIST Sectoral indices, which are inactive or could not be consistently aligned with the GCPU, were excluded from the dataset to maintain the integrity of the analysis.

The GCPU data used in this study are obtained from the database provided by Ma et al. (2024). The weekly stock market data of BIST sectoral indices are retrieved from Refinitiv (2025). Table 1 provides insight into the variables of the study.

Table 1. Key Variables

Variable	Name	Relevance	Short Form
Independent Variable	Global Climate Policy Uncertainty Index	Index measures global uncertainty ambient climate-related policy decisions. Building via textual analysis of international news sources, index captures the frequency of terms related to climate, policy, and uncertainty (Ma et al., 2024).	GCP U
Dependent Variables	BIST Electricity Index	The electricity sector may be directly affected by climate policies, particularly due to its reliance on traditional energy sources and growing integration of renewable sources. Instruments such as carbon taxes, emissions trading, and incentives can make the index sensitive to policy uncertainty.	XEL KT
	BIST Chemical Petrol Plastic	This index is associated with environmental problems such as toxic waste and greenhouse emissions, generally subject to restrictive regulations. Uncertainty in future climate policies may influence compliance costs, gains, and investment motivation.	XKM YA

Table 1. Continued

Dependent Variables	BIST Electricity Index	The electricity sector may be directly affected by climate policies, particularly due to its reliance on traditional energy sources and growing integration of renewable sources. Instruments such as carbon taxes, emissions trading, and incentives can make the index sensitive to policy uncertainty.	XELKT
	BIST Chemical Petrol Plastic	This index is associated with environmental problems such as toxic waste and greenhouse emissions, generally subject to restrictive regulations. Uncertainty in future climate policies may influence compliance costs, gains, and investment motivation.	XKMYA
	BIST Basic Metal	Steel and aluminum industries are major carbon emitters and energy consumers. Climate-related attempts in worldwide can affect competitiveness and trade activity, making this sector vulnerable to climate policy uncertainty.	XMANA
	BIST Services	The environmental footprint of the services sector is relatively limited compared to carbon intensive sectors. However, certain parts of sector such as transportation, tourism, and logistics may expose to climate related regulations and operational risks.	XUHIZ
	BIST Financials	Although financial institutions have no direct emissions, they can still be affected through their investments in carbon-intensive sectors. In addition, climate finance regulations and ESG disclosure requirements may increase their exposure to transition risks and changing investor behavior.	XUMALI
	BIST Industrials	This broad category contains diverse manufacturing sub-sectors with varying energy usage and emission levels. As pressures for environmental regulations and energy transition increase, the sector is likely to more sensitive to shifts in global climate policy and regulatory factors.	XUSIN
	BIST Technology	The technology sector has low direct emissions yet it can incur notably energy costs via data centers, servers, or cloud services. Moreover, it contributes climate related innovations. These two aspects make it important for exploring the impacts of policy uncertainty.	XUTEK
Control Variables	USD/TRY	The exchange rate reflects a common risk channel that conveys the effects of global and domestic market conditions to stock performance. In many countries, exchange rate movements are seen as an indicator of risk appetite and general market-wide shocks that simultaneously affect stock market sectors. To isolate the specific impact of GCPU on sectoral stock performance, the exchange rate return (\$/₺) is added to the QR model as a control variable.	EXCR
	Volatility Index	The volatility index is a widely used indicator of global investor sentiment and reflects volatility expectations in U.S. stock markets using derivatives data. Including VIX as a control variable helps to one can understand to broad market risk and shocks, making it possible to identify the specific impact of GCPU on sectoral returns.	VIX

Ma et al. (2024) developed the GCPU index using three alternative aggregation methods: (1) GDP at current prices, (2) GDP adjusted for purchasing power parity (PPP), and (3) equal weighting. Their CPU index is designed based on data from twelve countries, which are Australia, Brazil, Canada, China, France, Germany, India, Japan, Korea, South Africa, the United Kingdom, and the United States. Most of these countries are classified as developed or major emerging economies. At this stage, it is important to select the version that best captures GCPU for a country like Türkiye, which is not part of the core but remains globally integrated. Countries such as the U.S., China, and Germany are central in shaping climate policies and determining their worldwide

implications. In addition, these countries have the greatest effect on economically integrated countries like Türkiye.

Therefore, a GCPU weighted by the relative size of these major economies provides a more reliable indicator for detecting the effects of global climate policies on Turkish sectoral stocks. Consequently, this study uses the weekly GCPU data weighted by GDP at current prices in logarithmic form. Subsequently, weekly returns of the price series are calculated using the following formula:

$$r_t = \ln(P_t) - \ln(P_{t-1}) = \ln(P_t/P_{t-1}) \quad (1)$$

where, r_t indicates the return of the sectoral price indices in week t . P_t and P_{t-1} represent the stock price of the indices in week t and week $t - 1$, respectively. Table 2 reports the descriptive statistics of the variables together with the results of unit root tests to assess their stationarity properties.

Table 2. Descriptive Statistics

	GCPU	XELKT	XKMYA	XMANA	XUHIZ	XUMALI	XUSIN	XUTEK	EXCR	VIX
Mean	4.420	0.002	0.004	0.004	0.003	0.003	0.004	0.003	0.003	19.780
Median	4.491	0.003	0.005	0.006	0.005	0.005	0.006	0.006	0.001	17.545
Maximum	5.932	0.354	0.253	0.245	0.242	0.319	0.211	0.280	0.420	79.130
Minimum	1.287	-0.351	-0.206	-0.255	-0.351	-0.315	-0.257	-0.311	-0.351	9.140
Std. Dev.	0.677	0.049	0.043	0.051	0.039	0.050	0.038	0.050	0.029	8.676
Skewness	-0.818	-0.446	-0.163	-0.417	-0.647	-0.205	-0.686	-0.415	2.574	2.257
Kurtosis	4.057	10.837	6.122	5.870	11.56	7.838	8.067	8.252	62.766	11.262
J&B	193.0	3163.0	501.0	454.2	3810.2	1198.8	1401.0	1437.8	182926.9	4506.7
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observation	1220	1220	1220	1220	1220	1220	1220	1220	1220	1220
ADF (C&T)	-8.11***	-33.48***	-34.31***	-34.31***	-33.98***	-22.86***	-33.23***	-22.30***	-17.82***	-6.71***
PP (C&T)	-34.95***	-33.64***	-34.32***	-34.39***	-33.98***	-35.06***	-33.30***	-33.57***	-40.37***	-6.35***

Note: *** indicates statistical significance at the 1% level.

Table 2 provides summary statistics for weekly GCPU and stock returns over the 2000–2023 period, along with the results of the Jarque-Bera test for normality and unit root tests. The findings indicate that the variables are not normally distributed, suggesting the presence of outliers in the time series. This, in turn, justifies the use of quantile regression as a more robust approach, given the inflexibility of traditional models in handling such deviations. All variables are also found to be stationary at the level when both trend and intercept are included. Figure 1 illustrates the time series graphs of the variables used in the study.

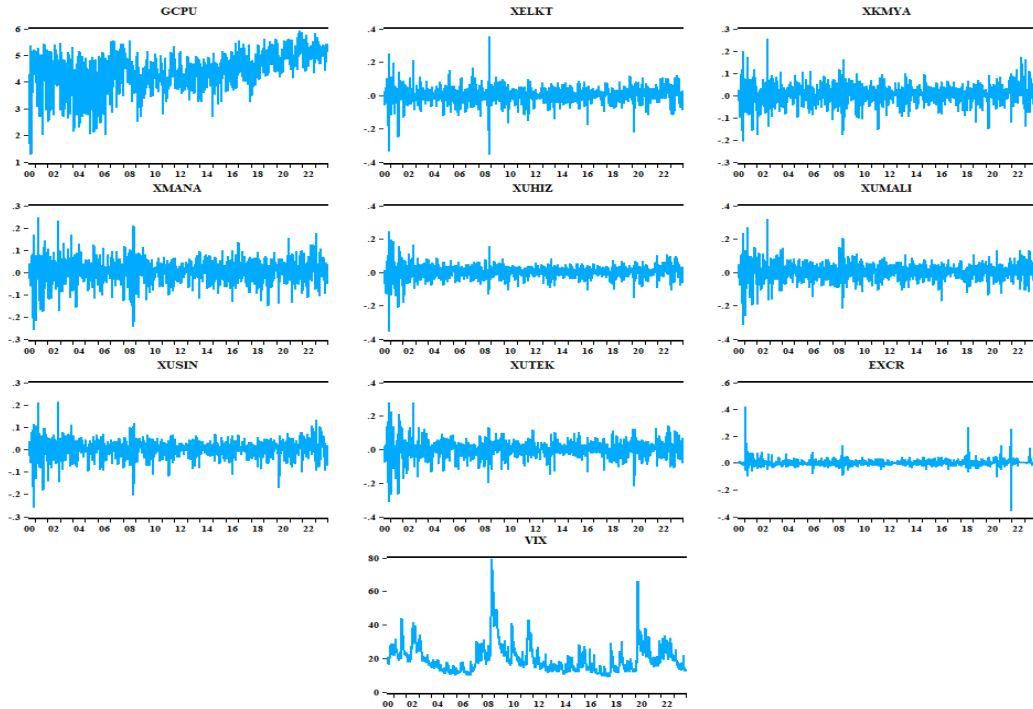


Figure 1. Time Series Plots of Variables

To determine the effect of GCPU on Turkish sectoral stock returns under different market regimes, this study employs a quantile regression approach. Quantile regression estimates the link between independent variables and certain quantiles of the dependent variable, without imposing distributional assumptions in the error terms. It is especially advantageous when classical assumptions such as homoscedasticity are violated or when the focus is on the tails of the distribution (Waldmann, 2018). Furthermore, it is well-suited for time series containing outliers. Quantile regression focuses on specific parts (quantiles) of the conditional distribution of the dependent variable, and estimates how explanatory variables affect different points (e.g., the median or the tails) of that distribution. The general form of QR model in this study is described by the following equation:

$$Q_{R_{i,t}}(\tau|X) = \alpha_i(\tau) + \gamma_i(\tau)GCPU_t + \beta_i(\tau)EXCR_t + \eta_i(\tau)VIX_t \quad (2)$$

where $Q_{R_{i,t}}(\tau|X)$ denotes the conditional quantile of the weekly stock market returns for sector i at quantile level τ . $R_{i,t}$ represents the weekly stock returns of sector i . The coefficient $\gamma_i(\tau)$ captures the effect of the $GCPU_t$ index on sectoral returns at the τ^{th} quantile. $\beta_i(\tau)$ reflects the impact of the weekly exchange rate return, while η_i measures the sensitivity of sectoral returns to the volatility index. Both control variables are included in the model to separate the effect of GCPU from general market-wide risk factors. To examine the impact of GCPU on Turkish sectoral returns within various market states, this study considers multiple quantiles of each sector's return distribution. Relying on weekly data, the variables are specified without lags, allowing us to observe immediate market responses.

4. Empirical Results

The study focuses on the effects of GCPU on Turkish sectoral stock returns. The sample consists of 1220 weekly observations for each variable. Quantile regression is robust to heteroscedasticity, but to be on the safe side, this study applies bootstrap standard errors using the XY-pair resampling technique to ensure reliable outputs. Results are reported in Table 3. According to the results, GCPU has a significant and positive effect on Turkish sectoral returns across different quantiles. This effect also varies between lower and upper quantiles in certain sectors.

For the BIST Electricity sector, which largely comprises stocks of fossil and renewable energy firms, the GCPU shows a significant positive effect at the 15th to the 80th quantile and the 95th quantile. From a quantile regression perspective, this pattern indicates that the impact of GCPU on Turkish electricity stocks is almost uniform across the return distribution. Specifically, the persistent positive effect between the 15th and 70th quantiles further implies that during neutral to moderately favorable market conditions, global climate uncertainty continues to serve as a supportive factor for Turkish energy stocks’ performance. However, the absence of statistical significance in the upper tails of the return distribution indicates that in strong bullish markets, the marginal influence of climate policy uncertainty becomes less pronounced except for the last quantile.

In the BIST Chemical, Petroleum, and Plastic sector (XKMYA), the GCPU only has a strong and significant positive effect in the middle and upper quantiles (from 55th to 85th). From this standpoint, this finding implies that GCPU is fruitful in the sector during strengthening bullish market conditions. In such periods, investors may anticipate that heightened climate-related policy actions such as regulations, carbon pricing, or taxation advantages for cleaner production could increase demand for innovative materials, alternative energy inputs, or adaptation technologies therein the sector. The weak or insignificant effects in the lower and middle quantiles suggest that under neutral or bearish market conditions, the BIST Chemical sector performance is less sensitive to climate policy uncertainty.

The GCPU exerts a negative effect on stock returns up to the 45th quantile; however, no significant effect is observed across these quantiles in the BIST Basic Metal (XMANA) sector. This suggests that during bearish or relatively weak market conditions, heightened GCPU exerts downward pressure on basic metal returns, possibly due to concerns over stricter emission regulations, increased production costs, or reduced global demand for energy-intensive commodities. Since this sector is highly integrated with global markets, its response is broadly consistent with international evidence, reflecting its vulnerability to global demand shocks and climate-related regulatory risks. The only strongly significant positive effect was observed at the 95th quantile may point out that GCPU is perceived less as a risk and more as a sign of future structural demand for metals driven by global green transition policies.

Table 3. Model Results

Quantile	XELKT	XKMYA	XMANA	XUHIZ	XUMALI	XUSIN	XUTEK
0,05	0.005272 (0.84)	0.007018 (1.39)	0.005406 (0.70)	0.010144** (2.18)	0.005145 (0.83)	0.001913 (0.32)	0.014347* (1.87)
0,10	0.005289 (1.59)	0.003285 (0.91)	-0.001124 (-0.29)	0.002064 (0.42)	0.000740 (0.19)	0.004484 (1.39)	0.007576* (1.67)
0,15	0.009554*** (3.88)	0.004490* (1.79)	-0.000457 (-0.16)	0.001474 (0.53)	0.001331 (0.42)	0.002048 (0.74)	0.008166** (2.28)
0,20	0.010330*** (4.96)	0.003808 (1.64)	-0.001785 (-0.64)	0.003417 (1.37)	0.002217 (0.75)	0.002253 (1.03)	0.007649** (2.21)
0,25	0.008304*** (3.32)	0.002564 (1.19)	-0.001539 (-0.63)	0.002383 (1.15)	0.003193 (1.21)	0.002591 (1.08)	0.006071* (1.88)
0,30	0.008505*** (3.50)	0.002665 (1.21)	-0.001457 (-0.51)	0.002945 (1.50)	0.003635* (1.93)	0.000333 (0.14)	0.006021** (2.07)
0,35	0.006311*** (2.59)	0.002809 (1.31)	-0.001255 (-0.50)	0.002564 (1.24)	0.003343 (1.48)	0.000404 (0.19)	0.005343* (1.87)
0,40	0.006095*** (2.91)	0.001622 (0.79)	-0.002073 (-0.85)	0.003092** (2.07)	0.003532 (1.57)	0.001478 (0.73)	0.002724 (1.10)
0,45	0.005272*** (2.77)	0.003268* (1.66)	-0.001295 (-0.53)	0.003154** (2.17)	0.004254* (1.95)	0.001695 (1.14)	0.003177* (1.71)
0,50	0.004945*** (2.65)	0.004203** (2.76)	0.001463 (0.66)	0.003789** (2.54)	0.003826* (1.72)	0.001744 (1.15)	0.004265** (2.39)
0,55	0.005402*** (2.97)	0.005015*** (3.34)	0.003326** (2.01)	0.004274*** (2.72)	0.004278** (2.08)	0.002150 (1.46)	0.002844 (1.54)
0,60	0.005877*** (3.22)	0.005937*** (4.20)	0.003935* (1.96)	0.003125* (1.70)	0.005025*** (3.02)	0.002986** (2.21)	0.002852 (1.33)
0,65	0.005585*** (2.99)	0.005338*** (2.98)	0.004708* (1.93)	0.001894 (1.05)	0.005347*** (3.08)	0.004023** (2.45)	0.000922 (0.35)
0,70	0.006429*** (3.17)	0.006491*** (3.19)	0.002934 (1.21)	0.002112 (1.23)	0.004306** (2.22)	0.003584** (2.16)	0.002054 (0.77)
0,75	0.005213** (2.18)	0.005894*** (3.05)	0.003319 (1.36)	0.003444* (1.70)	0.005069** (2.35)	0.004310*** (2.81)	0.001953 (0.79)
0,80	0.005265** (2.15)	0.005872*** (2.60)	0.003137 (1.19)	0.002460 (1.44)	0.003067 (1.08)	0.003955** (2.28)	0.002252 (0.99)
0,85	0.003576 (1.18)	0.006382*** (2.09)	0.004297 (1.51)	0.001625 (0.77)	0.004523 (1.49)	0.004359** (2.19)	0.002995 (1.11)
0,90	0.004125 (0.94)	0.005646** (2.14)	0.005234 (1.38)	0.004017 (1.54)	0.006324** (2.07)	0.003898 (1.54)	0.006079** (2.04)
0,95	0.009492* (1.85)	0.006221 (1.39)	0.011299*** (2.78)	0.004227 (1.44)	0.005129 (1.26)	0.008765*** (2.75)	0.008187 (1.56)

Note: *, **, and *** denotes statistical significance of GCPU at the 0.1, 0.05 and 0.01 level, respectively. t statistics are in parenthesis

For the BIST Services sector (XUHIZ), the GCPU has a positive and significant effect on returns in certain quantiles, particularly under bearish market conditions (5th quantile) and moderate market conditions (40th to 55th quantile). This behavior suggests that GCPU may support sectoral returns across varying market states. The mixed structure of this sector may also cause offsetting effects, as some sub-industrials could benefit from climate-related actions, while others might be adversely affected. Hence, the result likely discloses the combined influence of heterogeneous sectoral responses in the index rather than a uniform reaction across all services-related firms.

BIST Financial sector (XUMALI), on the other hand, GCPU generates a significant positive effect on stock returns, mainly in the middle to upper quantiles. This suggests that under moderate to bullish market conditions, investors may view GCPU as manageable or even as an opportunity. Thus, this response seems to depend on market conditions, with stronger effects when markets are neutral or favorable.

In the BIST Industrial sector (XUSIN), the GCPU has almost no significant effect in the lower quantiles. The effects become more explicit at the upper quantiles, with positive and significant coefficients from the 60th to 85th and 95th quantiles. This pattern observed from QR, suggests that during moderately strong to bullish market conditions, raising GCPU tends to support BIST industrial sector returns, indicating expectations of potential higher demand for industrial goods and infrastructure projects associated with climate adaptation and mitigation. In contrast, under weaker market conditions, GCPU does not play a role to determining industrial stock returns.

For the BIST Technology sector (XUTEK), the GCPU shows a positive and significant effect in the lower and middle quantiles, indicating that under bearish or moderately stressed market conditions, climate policy uncertainty boosts technology stocks, likely because of investor perception of the sector as innovative and adaptable to shifting regulatory landscapes. However, the effect weakens and becomes insignificant in mid quantiles and in the upper quantiles (55th to 85th). This suggests that in strong bullish markets, climate policy uncertainty does not turn into additional gains for technology stocks, and may even be viewed as a limiting factor on growth expectations. Figure 2 illustrates the results for each sector index.

Figure 2 visualizes the results from quantile regression, where the blue line symbolizes the estimated quantile coefficients, and the orange line represents the bootstrap confidence intervals. The horizontal axis denotes the quantiles, while the vertical axis denotes the coefficients. Accordingly, confidence intervals do not include zero; the effects at those quantiles are statistically significant. In general, the empirical evidence supports the thought proposed in the research, demonstrating that GCPU exerts heterogeneous effects across sectors in Borsa Istanbul. Thus, each sector exhibits distinct reactions, highlighting the importance of considering sectoral sensitivities when assessing the financial implications of CPU.



Figure 2. Quantile Estimates

Figure 3 presents the quantile regression results for all sectors simultaneously with a comprehensive overview. Marked lines in the graph illustrate how GCPU impact differs across different quantiles for each sector, highlighting positive effects as well as their statistical significance. This visual summary enables comparison for sectoral sensitivities to climate policy uncertainty and makes it easier to identify which sector returns react more strongly under bearish, neutral, and bullish market conditions.

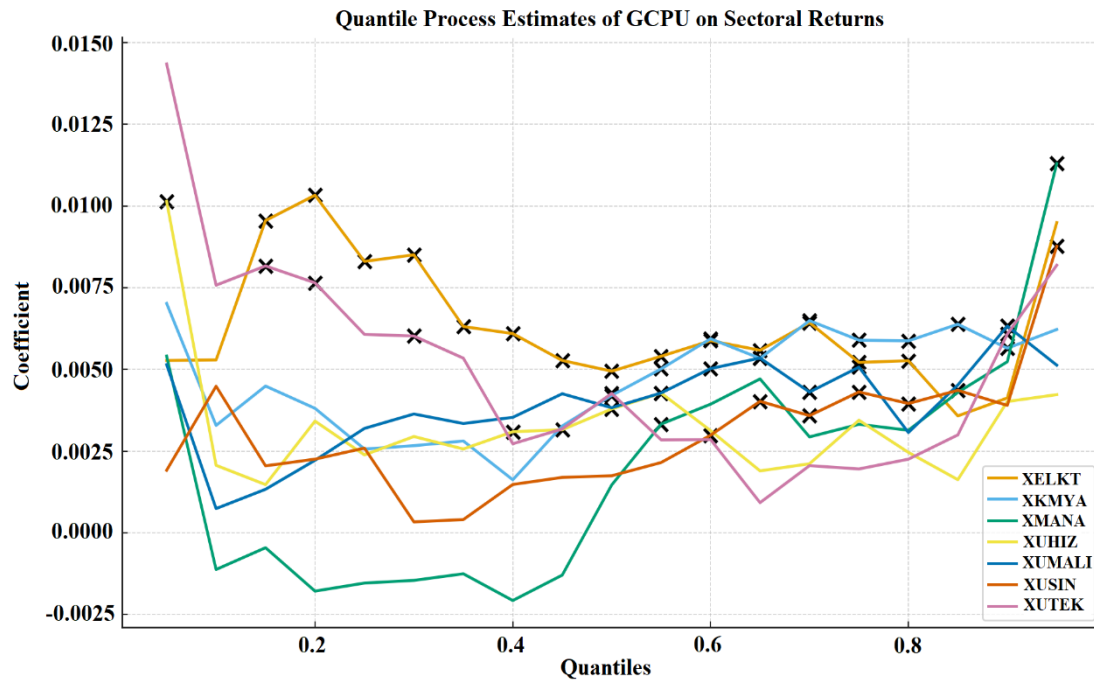


Figure 3. Quantile Process Estimates of GCPU on Sectoral Returns

Note: The × symbol indicates statistical significance at the 1% and 5% level at different quantiles.

According to Figure 3, as expected, the GCPU has the strongest impact the electricity sector, which includes both fossil and renewable energy firm stocks traded in Borsa Istanbul. Its effect on the BIST electricity sector index (XELKT) is positive at the 1% and 5% levels in many quantiles. These results suggest that climate policy uncertainty enhances BIST electricity sectoral returns, especially under normal market conditions. Interestingly, its influence seems to peak during bearish or bullish states. Such findings suggest that investors perceive the BIST electricity sector as a potential beneficiary of policy uncertainty, likely because of its direct link with renewable energy and transition-related expectations. GCPU also has a positive effect on both the BIST Chemical and BIST Industrial sectors at upper quantiles, meaning that climate policy uncertainty enhances sectoral returns exclusively during extreme bullish market conditions. This pattern may indicate investors’ perception of which sector could benefit from rising input costs or shifting demand dynamics associated with policy uncertainty, but only when overall market sentiment is highly optimistic. On the other side, in bearish market states, BIST Basic Metal and BIST Financial indices are not statistically affected by GCPU. The BIST Technology sector is also positively affected by GCPU at lower quantile levels, whereas the BIST Services sector shows the same response at middle quantiles.

These findings offer an understanding of market conditions and investor behavior while also highlighting the linkages between global policies on climate change and the Turkish stock market. According to the results, GCPU has limited effects in many sectors in terms of returns, especially during bearish states. One possible explanation might be that the dominance of other factors arising from extreme conditions, such as the 2007-08 global crisis and the Covid-19 pandemic. Furthermore, the analysis spanning 2000 to 2023 reveals the sensitivities of different sectors to GCPU, providing valuable insights for portfolio allocation and risk assessments by individual investors.

5. Conclusion

This paper analyzes the effects of GCPU on weekly stock returns of Borsa Istanbul using the data from 2000 to 2023. The study focuses on BIST sectoral indices due to their potential sensitivity to GCPU, and results point out that GCPU has significant effects on BIST sectoral returns. Quantile regression analysis shows that the effects of GCPU vary across sectors and different market states. Specifically, all sectors generally exhibit positive responses to GCPU across different market states. Results also show that the effect of GCPU is heterogeneous across market conditions, with specific sectors reacting more steadily to climate policy shocks and others showing sensitivity that depends on the current market state.

The interpretation of the results for the BIST Electricity (XELKT) sector is important, given that the index comprises both fossil and renewable energy shares. Although many renewable energy companies have conducted IPOs in Türkiye in recent years, fossil energy shares still constitute a large portion of the BIST Electricity Index. The effect of GCPU on energy stocks is significant and positive in almost all market states. Consequently, these results appear to diverge from the studies in the literature (Siddique et al., 2023; Di Tommaso et al., 2024; Iqbal et al., 2024; Tedeschi et al., 2024), particularly with respect to the Turkish stock market. Chemicals (XKMYA) and Industrials (XUSIN) also exhibit similar patterns in their responses to GCPU. Technology (XUTEK), on the other hand, is the most positively affected sector by GCPU, especially in times of bearish market conditions, a finding that closely parallels Pijourlet (2024) with regard to behavioral patterns of U.S. technology shares. Similarly, the Financial (XUMALI) and Services (XUHIZ) sectors show comparable dynamics under moderate market states. This finding is in line with Alharbey and Ben-Salha (2024), who argue that climate policy uncertainty has little effect during periods of sharp market swings but tends to play a more noticeable role when markets remain relatively stable in terms of stock returns. GCPU has a negative effect on Basic Metal (XMANA) returns in the lower quantiles, although this effect is statistically insignificant; conversely, in the highest quantile, GCPU shows a strong positive and significant effect on sectoral stock returns, which also differs from the previous literature.

To summarize, the empirical analysis shows that the GCPU influence is present in the Borsa Istanbul across different sectors and market states, even though controlling for common risk channels. In this context, using weekly stock market data structured in accordance with GCPU for a long period, results are consistent with the long-term patterns documented by Xu et al. (2023).

The findings of this study carry several implications for both retail and institutional investors, policy makers, and researchers by shedding light on how sectors are exposed to climate policy risks. For instance, effective portfolio allocation and risk management strategies should take into account these sector-specific sensitivities to climate policy uncertainty at the global level. Policy makers can also enhance transparency and predictability to reduce regulatory uncertainty and bolster investor confidence, especially in the climate-sensitive sectors. The findings obtained for Türkiye reveal that climate policy uncertainty at the global level exhibits different dynamics compared to the results of developed markets. Therefore, the results offer insights into global integration, local climate policies, and the composition of sectoral indices for Türkiye.

The study is limited to the absence of the CPU index created for Türkiye, as well as focusing solely on Turkish stock market returns. Future research could explore the firm-level data,

incorporating local CPU indices, or examine interactions with other financial assets. Researchers may also attempt to construct a CPU index specific to Türkiye. Besides, whether the effects of climate policy uncertainty on stock markets change across major events such as financial crises, health crises, or recent energy shocks may important research field. Finally, exploring the effects of climate-related risks on stock market volatility represents a promising avenue for future research.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher’s Contribution Rate Statement

I am a single author of this paper. My contribution is 100%.

Declaration of Researcher’s Conflict of Interest

There is no potential conflicts of interest in this study.

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EVALUATING CARBON AND ENERGY TAXATION PERFORMANCE IN BRICS-T COUNTRIES: AN INTEGRATED WENSLO–MCRAT APPROACH

BRICS-T Ülkelerinde Karbon ve Enerji Vergilendirme Performansının Değerlendirilmesi: Entegre Bir WENSLO–MCRAT Yaklaşım

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Abstract

Keywords:

Carbon
Taxation,
WENSLO,
MCRAT,
BRICS-T,
Environmental
Taxation,
Sensitivity
Analysis.

JEL Codes:

C61, H23, Q58

As global climate mitigation efforts intensify, carbon taxation has become a crucial policy tool to curb emissions and enhance fiscal-environmental sustainability. This study assesses the carbon and energy taxation performance of BRICS-T countries (Brazil, Russia, India, China, South Africa, and Turkey) using an integrated multi-criteria decision-making (MCDM) model combining WENSLO (Weights by ENvelope and SLOpe) and MCRAT (Multiple Criteria Ranking by Alternative Trace). Five indicators—Net Effective Carbon Rates (NECR), Net Effective Energy Rates (NEER), Net Energy Tax Revenues and Reform Potential (NETRRP), Revenue Forgone with NECR (RF+NECR), and Shares of Emissions Priced (SEP)—were selected to capture both fiscal intensity and environmental scope. WENSLO was used to derive objective weights, while MCRAT provided performance rankings. Findings indicate South Africa leads in overall performance, followed by India and China, with Brazil and Russia trailing. Sensitivity analysis identifies NECR and SEP as the most influential indicators, significantly impacting rankings. Rank reversal analysis reveals that Turkey’s relative position improves upon the removal of lower-performing countries. The study introduces a robust, data-driven framework for evaluating carbon taxation in emerging economies and offers strategic insights for enhancing climate-aligned fiscal policies.

Öz

Anahtar

Kelimeler:

Karbon
Vergilendirmesi,
WENSLO,
MCRAT,
BRICS-T,
Çevresel
Vergilendirme,
Duyarlılık
Analizi

JEL Kodları:

C61, H23, Q58

Küresel iklim değişikliğiyle mücadele çabalarının artmasıyla birlikte, karbon vergilendirmesi sera gazı emisyonlarını azaltmak ve mali-çevresel sürdürülebilirliği güçlendirmek adına önemli bir politika aracı hâline gelmiştir. Bu çalışma, BRICS-T ülkelerinin (Brezilya, Rusya, Hindistan, Çin, Güney Afrika ve Türkiye) karbon ve enerji vergilendirme performanslarını WENSLO (Weights by ENvelope and SLOpe) ve MCRAT (Multiple Criteria Ranking by Alternative Trace) yöntemlerinin bütünleştirildiği çok kriterli karar verme (ÇKKV) modeliyle değerlendirmektedir. Mali yoğunluk ve çevresel kapsamı yansıtan beş gösterge—Net Etkin Karbon Oranı (NECR), Net Etkin Enerji Oranı (NEER), Net Enerji Vergisi Gelirleri ve Reform Potansiyeli (NETRRP), Kayıp Gelir + NECR (RF+NECR) ve Fiyatlandırılan Emisyon Payı (SEP)—kullanılmıştır. WENSLO yöntemiyle nesnel ağırlıklar hesaplanmış, MCRAT ile ülkeler sıralanmıştır. Sonuçlara göre Güney Afrika en yüksek performansı gösterirken, onu Hindistan ve Çin izlemekte; Brezilya ve Rusya ise daha zayıf performans sergilemektedir. Duyarlılık analizi, NECR ve SEP kriterlerinin sıralamalar üzerindeki etkisinin yüksek olduğunu ortaya koyarken; sıra değişim analizi, düşük performanslı ülkelerin dışlanması durumunda Türkiye’nin göreceli konumunun iyileştiğini göstermektedir. Bu çalışma, gelişmekte olan ekonomilerde karbon vergilendirme performansını nesnel ve veri temelli bir yaklaşımla değerlendiren özgün bir çerçeve sunmaktadır.

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1. Introduction

Various measures have been taken to reduce the negative environmental and economic impacts of global warming. The most important and first international step in this context was taken at the United Nations Conference on Environment and Development held in Rio de Janeiro in 1992 (Özsoy, 2022; Yolal, 2025). At the summit, two important agreements were adopted to reduce greenhouse gas emissions: the Kyoto Protocol and the Paris Agreement. The Paris Agreement was adopted as a legally binding agreement by 196 countries and entered into force in 201. The agreement included carbon taxation as a tool against climate change (Timilsina, 2022). Carbon taxes, one of the main tools of carbon pricing, were first implemented in the energy sector. This practice, which began in the 1990s in the Scandinavian countries and was later adopted by Switzerland in 2008, spread to developing countries such as South Africa, Mexico, Chile, and India in the 2010s (Khastar et al., 2020). In this context, the Pigouvian tax, a carbon tax, aims to reduce emissions by internalizing environmental externalities and promoting renewable energy (Meng and Yu, 2023). A well-designed carbon tax contributes to emission reductions and economic efficiency (Pomerleau and Asen, 2019) and provides a “double win” by reducing distortionary taxes (Fay et al., 2015). These early applications highlight the need to examine the policy objectives of carbon taxes and their cross-country variations.

Carbon taxes usually include the costs of CO₂ emissions; however, the goals of these levies can be different in different countries. These taxes mainly aim to cut down on greenhouse gas emissions, send signals to the market, and bring in money for the government (Sumner et al., 2011; Yolal, 2025). Their main strategies are to make tax changes that cut down on emissions while boosting growth, put money into low-carbon technologies, and help people who are hurt by high carbon costs. The four main ideas behind carbon taxes are: 1) the polluter pays, 2) prevention, 3) common but different responsibilities, and 4) fairness and appropriate punishment (United Nations, 2021). Carbon taxes are a significant method for generating revenue to tackle global emissions (Özbek, 2019). This situation has turned this subject into a major area of research. In this context, the current study aims to assess the effectiveness of carbon and energy taxation in BRICS-T economies, utilizing WENSLO and MCRAT for a comparative and data-driven policy analysis. However, despite these targets, quantitative evidence on the actual impact of carbon taxes is limited.

Despite increasing research on carbon taxation, most comparative studies use qualitative assessments or nominal tax rates. Therefore, we lack sufficient information about the effectiveness of carbon taxation for both the environment and the economy. Furthermore, modern research rarely uses objective weighting techniques to assess the importance of various criteria. To address these shortcomings, this study provides a comprehensive, data-based assessment of the effectiveness of energy and carbon pricing in BRICS-T economies through the integration of the WENSLO and MCRAT methodologies. It contributes to the academic literature by providing empirical data for practitioners and policymakers in developing economies seeking to establish carbon pricing frameworks. Therefore, our study combines objective weighting and multi-criteria evaluation methods to fill these gaps.

Two MCDM methods were used in this study: MCRAT (Multiple Criteria Ranking by Alternative Trace) and WENSLO (Weights by ENvelope and SLOpe). This study makes several significant contributions to the current body of research. The WENSLO-MCRAT model, which has never been used in this policy context before, offers a new and impartial way

to measure how well carbon and energy levies work in the BRICS-T economies. Second, objective weighting (WENSLO) makes the evaluation of carbon policy more methodologically sound by removing any bias that might come from personal opinions about the value of criteria. Third, the study gives us a better idea of how well carbon taxes work by putting together economic and environmental data into a multi-criteria framework. A two-stage sensitivity analysis improves the reliability and robustness of the findings, making them more useful for policymakers looking for data-driven information about how to put the carbon price into effect.

2. Literature Review

Carbon dioxide, which accounts for approximately 80% of the world's ever-increasing greenhouse gas emissions, and the climate change it causes have become a significant problem. Carbon taxes, an important policy tool for reducing both the economic and environmental impacts of climate change, have gained considerable importance. The literature contains numerous studies supporting the critical functions of carbon taxes. Studies conducted in the ASEAN region by Solaymani (2017) and Yahoo and Othman (2017) have shown that well-structured, revenue-neutral carbon taxes can reduce emissions by limiting economic activity. This supports the idea of a "double win." Studies in Sweden and Indonesia (Shmelev and Speck, 2018) confirm the effectiveness of carbon taxes in reducing emissions. They are also influenced by macroeconomic influences, technological advances, and sectoral differences.

Empirical results from North America and Europe can be used to supplement the existing literature on carbon tax implementation. Çakmak (2018) found that British Columbia's carbon tax between 2008 and 2015 promoted both economic growth and emission reductions. Jin et al. (2018), using a Data Envelopment Analysis (DEA) model, showed that higher tax rates can promote environmentally friendly production processes. Fernando (2019) found a 52 tonne per capita reduction in CO₂ emissions in the Nordic countries between 1990 and 2004. Sweden is a good example: Andersen (2019) discovered an 11% reduction in CO₂ emissions from transportation between 1990 and 2005; Ercořkun and Kovancılar (2023) also noted that channeling carbon tax revenues to environmental innovation provides both fiscal and ecological benefits. Martinsson et al. (2024) and Mideksa (2024) found that higher carbon tax rates and a shift to clean energy led to emissions reductions of up to 31% in Swedish manufacturing. Finland achieved the same reduction rate in 2005. Consistent with previous studies (Mideksa, 2024; Martinsson et al., 2024), Yolal (2025) emphasized the importance of optimal timing for the implementation of carbon taxes to prevent the erosion of competitiveness. These studies confirm that carbon taxes are effective in reducing emissions, but note that findings may vary depending on policy design, exemption strategies, and specific institutional frameworks.

In recent years, scholars have been examining the complex and multidimensional aspects of carbon taxes and climate policies using stakeholder-focused analytical frameworks and multi-criteria decision-making (MCDM) techniques. In a 2022 study, Chelly and colleagues evaluated different carbon tax scenarios, proposed four different multi-period technology selection models, and demonstrated that the timing of green investments depends more on targeted carbon prices than on the type of tax. Finally, Ratanakuakangwan and Morita (2022) integrated multiple evaluation criteria such as cost, emissions, social impacts, employment, and energy security in a sensitivity analysis-based model in Thailand and found that the most effective

policies are those that prioritize environmental and social objectives rather than cost-driven approaches.

While the existing literature provides important insights into the environmental and economic impacts of carbon taxes, it suffers from several limitations. Many empirical studies are either confined to a single country context or rely on static econometric models to fully capture the multidimensional nature of the tax. Furthermore, research analyzing the relative importance of fiscal and environmental factors and applying objective weighting methods is quite limited. Another major problem is that there aren't many comparative assessments of rising economies, especially BRICS-T countries. This study seeks to rectify these deficiencies by amalgamating the WENSLO and MCRAT methodologies inside a data-driven framework. Aside from the new methods, the research's most important contribution is showing how an objective, multi-criteria assessment can lead to useful policy changes for developing countries. The analysis enhances the existing discourse regarding the formulation of a balanced carbon pricing system that reconciles environmental taxation, fiscal reform, economic growth, and decarbonization goals by pinpointing the structural and financial determinants that significantly impact tax performance.

3. Methodology

This research evaluates the efficacy of energy and carbon taxes in the BRICS-T economies through an MCDM technique. The WENSLO method was used to make sure that the assessment criteria weighing process was fair. This method only uses the inherent features and distributions of the data to set the criterion weights, not expert opinion or subjective inputs. After the goal weights were set, MCRAT was used to rank the countries depending on how well they did overall on the given criteria.

A two-stage sensitivity analysis was conducted to assess the robustness and reliability of the findings. The weights of each criterion were systematically varied in the first stage to assess the impact of changes in individual importance on the final rankings. In the second stage, rank reversal analysis was used to determine how well the model performed under different conditions where items were removed. This meant eliminating the worst-performing option and restarting the rankings.

The next section discusses the dataset and the initial decision matrix created for the study. The WENSLO and MCRAT techniques are also described in detail.

3.1. WENSLO Method

The basic methods used by the WENSLO method to calculate the criteria weights will be discussed in the next section (Pamucar et al., 2024).

Step 1. Construct the decision matrix.

$$[x_{ij}]_{m \times n} = \begin{bmatrix} A/C & C_1 & C_2 & \dots & C_n \\ A_1 & x_{11} & x_{12} & \dots & x_{1n} \\ A_2 & x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ A_m & x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

where:

x_{ij} denotes the performance of the i . alternative concerning the j . criterion.

$A_1, A_2, \dots, A_m$ denotes an option vector space.

m denotes the number of options.

$C_1, C_2, \dots, C_n$ represents a vector space of criteria.

n denotes the quantity of criteria.

Step 2. The input data are normalized to obtain a dimensionless decision matrix. The following equation is used for linear normalization:

$$z_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}}, \forall j \in [1, 2, \dots, n] \quad (2)$$

The normalized decision matrix is presented as follows:

$$Z(A, C) = [z_{ij}]_{m \times n} = \begin{bmatrix} A/C & C_1 & C_2 & \dots & C_n \\ A_1 & z_{11} & z_{12} & \dots & z_{1n} \\ A_2 & z_{21} & z_{22} & \dots & z_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ A_m & z_{m1} & z_{m2} & \dots & z_{mn} \end{bmatrix} \quad (3)$$

In the normalized decision matrix Z , each element z_{ij} satisfies the condition $0 < z_{ij} < 1$.

Step 3. In this step, class intervals for each criterion are determined using Sturges' rule to support objective weight calculation.

$$\Delta z_j = \frac{\max_{1 \leq i \leq m} z_{ij} - \min_{1 \leq i \leq m} z_{ij}}{1 + 3.322 \times \log(m)}, \quad \forall j \in [1, 2, \dots, n] \quad (4)$$

Step 4. The slope of each criterion is calculated using the following equation:

$$\tan \varphi_j = \frac{\sum_{i=1}^m z_{ij}}{(m-1) \times \Delta z_j}, \quad \forall j \in [1, 2, \dots, n] \quad (5)$$

Step 5. The envelope of each criterion is determined by calculating the total Euclidean distance between its initial and final normalized values, as shown in Equation (6).

$$E_j = \sum_{i=1}^{m-1} \sqrt{(z_{i+1,j} - z_{ij})^2 + \Delta z_j^2}, \quad \forall j \in [1, 2, \dots, n] \quad (6)$$

Step 6. In this step, the envelope-slope ratio is calculated by dividing the total Euclidean distance by the criterion slope, as defined in Equation (7).

$$q_j = \frac{E_j}{\tan \varphi_j}, \quad \forall j \in [1, 2, \dots, n] \quad (7)$$

Step 7. In this step, the final criterion weights are determined using the following equation.

$$w_j = \frac{q_j}{\sum_{i=1}^n q_j}, \quad \forall j \in [1, 2, \dots, n] \quad (8)$$

3.2. MCRAT Method

Urošević et al. (2021) introduced MCRAT, a new method for evaluating alternatives based on a matrix trace ranking system. It has many benefits, such as being clear, logical, applicable in many situations, and capable of handling stress. MCRAT is an MCDM method that compares options according to various criteria. It provides reliable, widely available, and proven results (Ulutaş et al., 2023). MCRAT facilitates the decision-making process by ranking options according to a number of variables. The recently developed MCRAT method has many advantages. The most important ones are that it is simple to use, has a logical structure, is well-supported, methodologically sound, and can be used in many different situations (Abdulaal and Bafail, 2022). The following illustrates how the method is implemented (Urošević et al., 2021):

Step 1. The decision matrix (B) is constructed using Equation (9).

$$B = [b_{ij}]_{m \times n} \quad (9)$$

Step 2. The decision matrix is normalized using Equations (10) for beneficial criteria and (11) for non-beneficial criteria.

$$b_{ij}^* = \frac{b_{ij}}{\max(b_{ij})} \quad (10)$$

$$b_{ij}^* = \frac{\min(b_{ij})}{b_{ij}} \quad (11)$$

Step 3. The weighted normalization values are calculated using Equation (12), and the weighted normalized matrix is presented in Equation (13).

$$v_{ij} = w_{jcomb} \times b_{ij}^* \quad (12)$$

$$V = [v_{ij}]_{m \times n} \quad (13)$$

Step 4. The ideal alternative is identified using Equation (14).

$$y_j = \max(v_{ij} \mid 1 \leq j \leq n) \quad (14)$$

The ideal alternatives are presented in the following set formulation:

$$Y = \{y_1, y_2, \dots, y_j\} \quad (15)$$

Step 5. This step involves dividing the ideal alternative into two subgroups using Equation (16), while Equation (17) defines the structure of the ideal alternative.

$$Y = Y^{max} \cup Y^{min} \quad (16)$$

$$Y = \{y_1, y_2, \dots, y_k\} \cup \{y_1, y_2, \dots, y_h\}; k + h = j, \quad (17)$$

where k denotes the number of criteria, and $h = n - k$ represents the number of remaining alternatives.

Step 6. This step involves decomposing the remaining alternatives using Equations (18) and (19).

$$K = K_i^{max} \cup K_i^{min} \quad (18)$$

$$K = \{k_1, k_2, \dots, k_{ik}\} \cup \{k_1, k_2, \dots, k_{ih}\} \quad (19)$$

Step 7. Equations (20) and (21) are employed to calculate each component of the magnitude of the ideal alternative.

$$Y_k = \sqrt{y_1^2 + y_2^2 + \dots y_k^2} \quad (20)$$

$$Y_h = \sqrt{y_1^2 + y_2^2 + \dots y_h^2} \quad (21)$$

The magnitude of each alternative is similarly calculated using the approach defined in Equations (22) and (23).

$$E_k = \sqrt{e_{i1}^2 + e_{i2}^2 + \dots e_{ik}^2} \quad (22)$$

$$E_h = \sqrt{e_{i1}^2 + e_{i2}^2 + \dots e_{ih}^2} \quad (23)$$

Step 8. Matrix T , which represents the components of the best possible alternative, is constructed using Equation (24).

$$T = \begin{bmatrix} Y_k & 0 \\ 0 & Y_h \end{bmatrix} \quad (24)$$

Step 9. Matrix S_i , representing the component of each alternative, is constructed using Equation (25).

$$S_i = \begin{bmatrix} E_{ik} & 0 \\ 0 & E_{ih} \end{bmatrix} \quad (25)$$

Step 10. Matrix Z_i is formulated using Equation (26).

$$Z_i = T \times S_i = \begin{bmatrix} z_{11;i} & 0 \\ 0 & z_{22;i} \end{bmatrix} \quad (26)$$

Step 11. The trace of matrix Z_i is calculated using Equation (27).

$$tr(Z_i) = z_{11;i} + z_{22;i} \quad (27)$$

3.3. Dataset

This study evaluates the performance of the BRICS-T economies concerning energy and carbon taxes using a structured framework of five variables. We carefully picked these criteria to show how well fiscal environmental programs work and how well they cover all the bases. The dataset includes Priced Emission Shares (SEP), which show the full range of carbon pricing, including market-based methods; Forgotten Revenue and Net Effective Carbon Rates (RF + NECR), which indicate issues such as simultaneous taxation and subsidies; Net Effective Carbon Rates (NECR), which measure how effectively carbon taxation operates; and Net Effective Energy Rates (NEER), which capture the overall tax burden on energy products. The WENSLO-MCRAT study is based on these criteria, which are based on both economic and environmental importance. This lets us make objective comparisons between countries in many different ways. All of the data used in this study came from the "Taxes and Environment" component of the OECD Data Explorer portal (OECD, 2023). Table 1 shows the criteria and their properties.

Table 1. Overview of the Criteria

Code	Criteria	Unit	Max/Min	Year
C1	Net Effective Carbon Rates	Euros per tonne of CO ₂ -equivalent	Max	2023
C2	Net Effective Energy Rates	Euros per gigajoule	Max	2023
C3	Net Energy Tax Revenues and Reform Potential	Total reform potential (Percentage of GDP)	Max	2023
C4	Revenue Forgone and Net Effective Carbon Rates	EUR 120 per tonne of CO ₂ e benchmark	Min	2023
C5	Shares of Emissions Priced	Above EUR 0 per tonne of CO ₂ e	Max	2023

Table 2 presents the initial decision matrix, which consists of the alternatives and their performance values with respect to each evaluation criterion.

Table 2. Rank Evolution of Alternatives Across Iterative Elimination Steps

Country	C1	C2	C3	C4	C5
Brazil	0.30	0.51	1.8	2.85	5.6
Russia	3.83	0.33	5.7	8.70	9.7
India	7.23	0.68	4.7	7.66	53.9
China	6.77	0.66	5.0	7.89	44.7
South Africa	13.78	1.36	6.3	10.34	34.9
Türkiye	7.57	0.75	2.1	3.46	31.4

Following the creation of the initial decision matrix, the weights of the criteria were determined using the WENSLO method. Then, the alternatives are ranked according to the MCRAT method. The next section presents the results of these methods and their related interpretations, respectively.

4. Analysis

The results of the integrated decision-making model that combines the MCRAT and WENSLO approaches are shown in this section. First, we go over the outcomes of using these techniques to evaluate the BRICS-T nations' performance in terms of energy and carbon taxes. The resilience and stability of the model outputs under various parameter settings and structural changes in the decision matrix are next evaluated using a two-stage sensitivity analysis.

4.1. Results of the Integrated WENSLO-MCRAT Model

The WENSLO approach was used to objectively ascertain each criterion's relative value in the evaluation process. Regardless of personal preferences, this method determines criteria weights by using the dataset's geometric and distributional properties. Specifically, the primary weighting element that reflected each criterion's sensitivity and discriminative capacity was the envelope-slope ratio. Table 3 displays the specific outcomes of the weight computation based on WENSLO.

Table 3. WENSLO-Based Results for Criterion Weight Determination

Criterion	Δz_j	Slope values	Envelope values	Envelope-slope ratio
C1	0.0974	2.0535	0.7478	0.3642
C2	0.0685	2.9202	0.5903	0.2021
C3	0.0501	3.9886	0.5184	0.1300
C4	0.0522	3.8286	0.5185	0.1354
C5	0.0765	2.6158	0.6013	0.2299

Figure 1 illustrates the normalized weights of the five evaluation criteria as determined by the WENSLO method. Among these, NECR emerges as the most influential criterion with a weight of 0.3431, indicating its dominant role in the overall assessment. This is followed by SEP (Shares of Emissions Priced) with a weight of 0.2165, and NEER (Net Effective Energy Rates) with 0.1904. The remaining two criteria, RF+NECR and NETRRP, have comparatively lower weights of 0.1276 and 0.1224, respectively. The distribution of weights suggests that carbon-specific fiscal measures (NECR) and comprehensive pricing mechanisms (SEP) are considered the most critical dimensions in evaluating carbon and energy taxation performance across the BRICS-T countries.

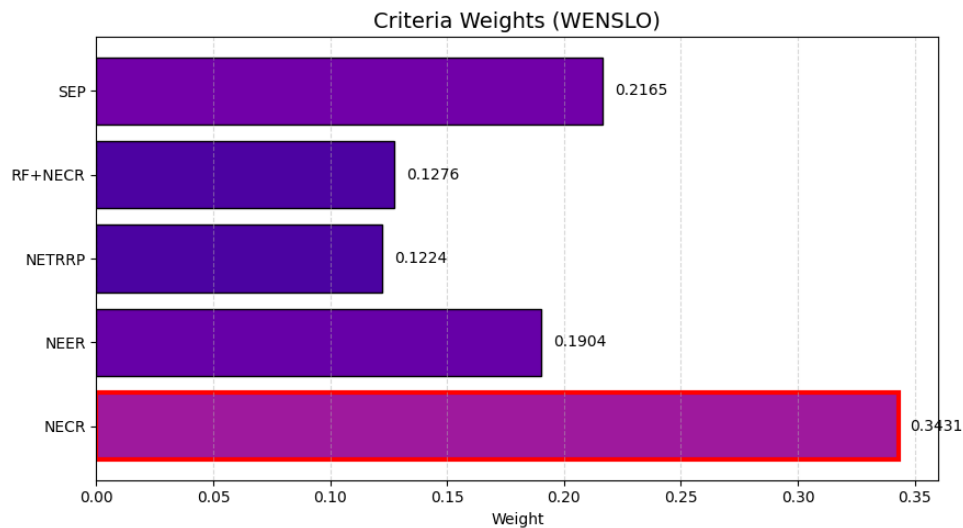


Figure 1. Final Criteria Weight Values

Following the determination of criterion weights using the WENSLO method, the MCRAT technique was employed to rank the BRICS-T countries based on their aggregated performance across all evaluation criteria.

Figure 2 presents the MCRAT scores for each country. As illustrated, South Africa ranks first with the highest composite score of 0.2062, indicating its relatively strong performance across the evaluated indicators. India follows with a score of 0.1505, slightly ahead of China (0.1362) and Turkey (0.1310). Russia and Brazil are positioned at the lower end of the ranking, with scores of 0.0788 and 0.0548, respectively. These results reflect notable disparities among the BRICS-T countries in terms of carbon and energy taxation performance, with South Africa emerging as the most robust performer in the current assessment framework.

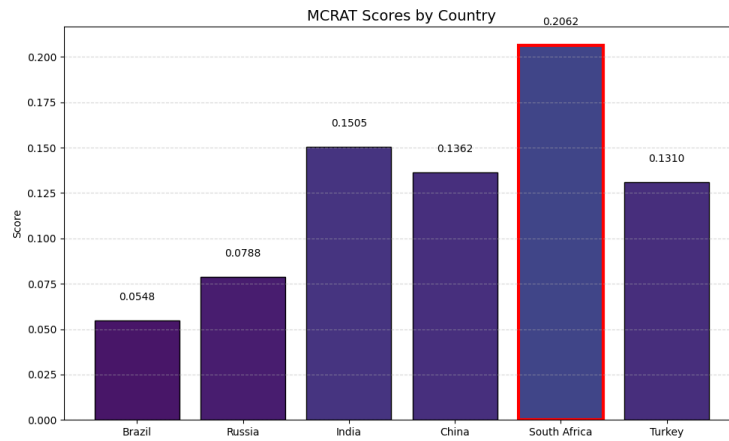


Figure 2. MCRAT-Based Performance Scores of BRICS-T Countries

4.2. Sensitivity Analysis

A comprehensive sensitivity analysis was carried out to evaluate the robustness of the final alternative rankings produced by MCRAT. In this analysis, the criterion weights initially calculated using WENSLO were systematically altered to observe how changes in individual criterion importance affect the overall decision outcome. Specifically, the weight of each criterion was incrementally varied from 0% to 100% in steps of 10%, while the remaining weights were proportionally adjusted to ensure the total weight sum remained normalized to 1. For each new weighting scenario, the MCRAT method was reapplied to the decision matrix to recalculate the scores and derive the updated rankings of all six alternatives. This process was repeated for all five criteria, resulting in a total of 330 unique ranking scenarios (11 weight levels $\times$ 5 criteria $\times$ 6 alternatives), allowing for a detailed examination of how sensitive each alternative’s rank is to variations in the relative importance of the criteria, namely NECR, NEER, NETRRP, RF+NECR, and SEP. The results are visualized in Figure 3.

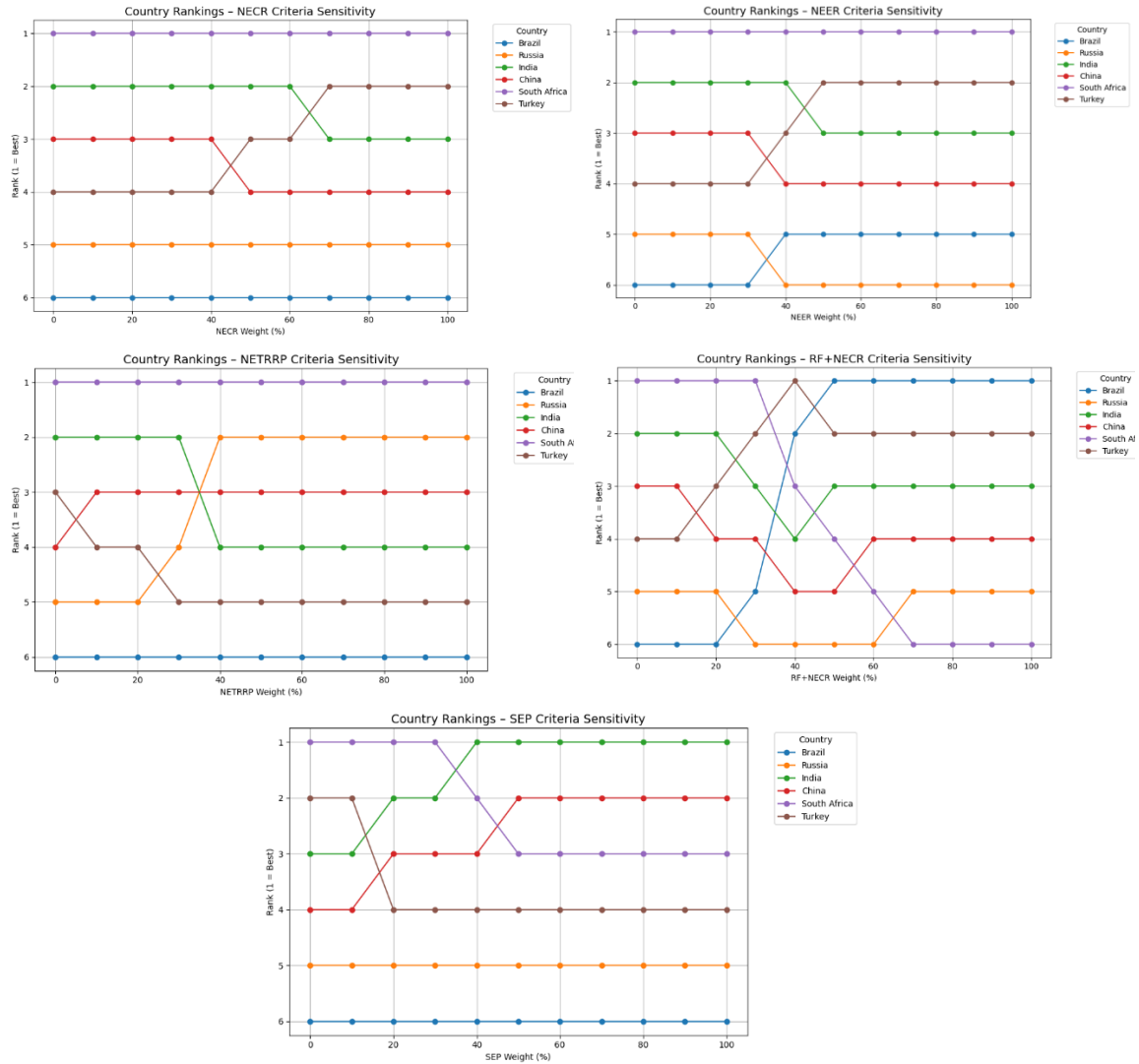


Figure 3. Ranking Variability Under Systematic Weight Adjustments for Each Criterion

The results indicate that the final rankings are highly sensitive to changes in the weights of certain criteria. In particular, NECR and SEP exhibit relatively high sensitivity, with significant fluctuations observed in the rankings of India, China, and South Africa. This highlights the strong influence of these two criteria on the overall evaluation. Similarly, NEER and RF+NECR show noticeable rank reversals, especially between China, India, and Turkey, reflecting how shifts in criterion importance can alter the relative positioning of these countries. In contrast, Brazil and Russia consistently maintain lower rankings across all weighting scenarios, indicating that their performance is comparatively weak and less responsive to individual criterion changes.

As a second stage of the sensitivity analysis, a rank reversal analysis was performed to evaluate the robustness and stability of the decision-making model, based on the initial rankings obtained through the MCRAT method and the criterion weights derived from the WENSLO technique.

In this analysis, the process began with all six alternatives (Brazil, Russia, India, China, South Africa, and Turkey). At each iteration, the alternative with the lowest performance score (i.e., the lowest MCRAT score) was systematically eliminated from the decision matrix. The WENSLO method was then reapplied to the reduced matrix to recalculate the criterion weights for the remaining alternatives, thereby simulating the impact of alternative removal on the weighting scheme. Subsequently, MCRAT was applied again using the updated weights to produce new scores and ranks.

This iterative elimination continued until only two alternatives remained. At each step, the performance scores and ranks of the remaining countries were recorded, allowing for a detailed examination of how the ranking of alternatives changed dynamically as weaker options were excluded. The results are presented in Table 4.

Table 4. Rank Evolution of Alternatives Across Iterative Elimination Steps

Country	Step 1		Step 2		Step 3		Step 4	
	Rank	Score	Rank	Score	Rank	Score	Rank	Score
Brazil	–	–	–	–	–	–	–	–
Russia	5	0.074092	–	–	–	–	–	–
India	2	0.149784	3	0.128222	3	0.133432	–	–
China	3	0.134884	4	0.127802	–	–	–	–
South Africa	1	0.196155	1	0.181371	1	0.174667	1	0.217114
Turkey	4	0.128623	2	0.140011	2	0.143934	2	0.203285

The results in Table 4 show how the rankings of the remaining countries change during the rank reversal analysis, which is performed by successively eliminating the lowest performing alternatives. In Step 0, Brazil was eliminated as it had the lowest performance score, followed by Russia as the second weakest alternative. From Step 1 onwards, five countries remained, and their rankings were recalculated at each iteration using updated WENSLO weights and MCRAT scoring.

South Africa has performed strongly and consistently in every situation during the elimination process, maintaining its top ranking and even raising its score in the final phase. By going from fourth in Step 1 to second in Step 4, Turkey demonstrates a notable improvement, suggesting that when poorer options are removed, its relative performance improves. China's performance, on the other hand, suffered, going from third in Step 1 to elimination in Step 3. India ranked second and third across the steps, maintaining a competitive but rather erratic performance.

According to the ranking development, South Africa performs the best overall under the iterative elimination approach, whereas Turkey does better under the reduced scenarios but looks pretty bad with the entire set. The stability and sensitivity of nation rankings based on alternative composition are better understood thanks to this dynamic approach.

The findings are also displayed in Figure 4, along with the corresponding heatmap visualization and the ranking progress through the elimination phases. A crucial component in confirming the stability and equity of the multi-criteria decision-making model was the explicit identification of alternatives whose rankings are affected by the existence or lack of other possibilities.

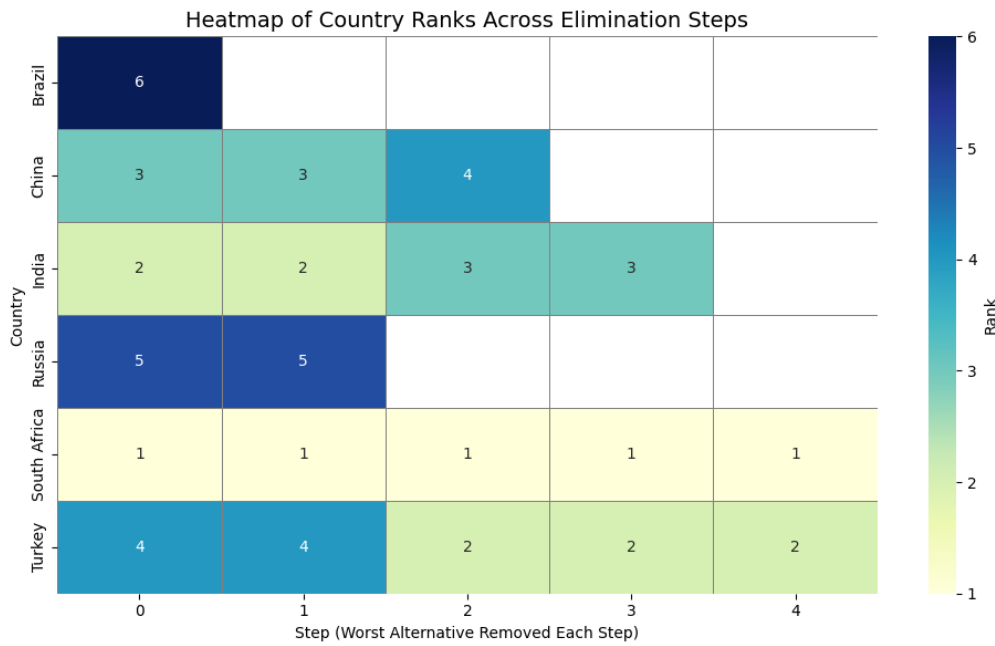


Figure 4. Ranking Variability Under Systematic Weight Adjustments for Each Criterion

5. Discussion

This study evaluates the BRICS-T nations' performance in terms of energy and carbon taxes using an integrated WENSLO-MCRAT multi-criteria decision-making framework. The WENSLO technique, which finds that SEP and Net Effective Carbon Ratios (NECR) are the most important criteria, was used to first determine the objective criteria weights. The MCRAT investigation found that Brazil and Russia had the lowest overall performance scores. South Africa usually had the greatest scores, followed by India. A comprehensive sensitivity analysis validated the rankings, underscoring the vulnerability of India, China, and Turkey to variations in the relative importance of various categories. The second-stage rank reversal study also proved that the model was stable. This showed that Turkey did much better as worse options were taken away, while South Africa stayed at the top of the rankings through all of the elimination rounds. These results show both the good and bad sides of the BRICS-T economies. They also show how useful and reliable the suggested way of making decisions is for looking at complicated policy areas like carbon taxes.

This study highlights the importance of the work by using a WENSLO-based analysis to prove the weights and examine the carbon taxation methods applied in the BRICS-T economies by NECR. NECR, which shows the actual cost of CO₂ emissions through both carbon taxes and emissions trading indicators, is a good option for policy measurement because it is a composite indicator. In a study by Boute (2024), it was stated that NECR is necessary for evaluating whether policies adopted by third countries are compatible with the climate targets set by the EU and, in particular, with practical tools such as the Carbon Border Adjustment Mechanism (CBAM). This situation has demonstrated that it is crucial to re-evaluate both climate governance and global trade rules, as well as national policies. Vesala (2023) noted that the historical development of NECR has gradually given it more leverage in reducing carbon emissions in Finland. The study found that countries with stricter carbon pricing strategies

performed better in carbon price assessments. Countries that performed well under high NECR conditions were India and South Africa in particular.

Sensitivity analysis results indicate that PKP and NECR have an impact on the rankings of South Africa, China, and India. This shows that performance rankings can change significantly when policymakers assign different weights to the components that influence them. Therefore, countries with medium-level performance may be stronger or weaker depending on the evaluation framework, and priority should be given to policy formulation.

Reversing the ranking in the study has helped to obtain more information about the structure of the decision model. This situation revealed how Turkey's ranking concealed comparisons with countries performing poorly and improved after weak preferences were removed. This demonstrated that using more than simple rankings affects the context and competitiveness assessment results and is quite essential.

From a policy perspective, the WENSLO-MCRAT model examined in this study is recognized as providing a solid foundation for the fair and impartial evaluation of carbon taxation solutions. The analysis used in this study has served as a guide for countries in developing carbon pricing strategies based on weight distributions and comparative effectiveness. Countries such as Turkey and India, in particular, can achieve successful performance by using and further developing their fiscal instruments using robust criteria such as PKP and NECR.

Comparing the progress of South Africa, India, and Turkey in establishing clear rules for developing country economies offers essential insights. South Africa's continued leadership demonstrates that successfully integrated carbon pricing can provide various environmental and financial benefits to other countries and serve as a model for them. India's performance is generally strong but has a fragile structure. This situation demonstrates that it will contribute both to the stability of policies aimed at providing more incentives within the scope of renewable energy and to increasing effective carbon rates. Turkey's gradual recovery is ensuring greater clarity in emissions-based tax structures, making fiscal and climate goals more aligned. Countries that are not performing well in this regard need to improve their effective carbon rates and broaden their tax base. The experience of all BRICS-T countries shows that consistent, transparent, and flexible carbon tax regimes are crucial for establishing long-term economic and environmental policies.

6. Conclusion and Suggestions for Future Research

The aim of this study was to evaluate the effectiveness of energy and carbon taxation in BRICS-T countries using a hybrid multi-criteria decision-making framework combining the WENSLO and MCRAT methodologies. The WENSLO method was used to weight objective criteria, and countries were ranked based on their performance across five different criteria. The analysis revealed that the economies of BRICS-T countries are very different. India and China outperformed South Africa, while Brazil and Russia performed the worst. These results were confirmed through sensitivity analysis and ranking reversal assessments. Furthermore, the NECR and SEP components were shown to have a significant impact on the final rankings.

From a policy point of view, the results clearly show that we need unified, clear, and complete carbon pricing systems. South Africa's great performance shows how important it is to

work together on energy and fiscal reforms. India's results are less impressive but still good, which shows how important it is to set good carbon rates and improve policy coordination. Türkiye's changing circumstances show how much can be gained from targeted fiscal restructuring and more specialized emissions-based tax systems. Brazil and Russia could do better, though, if they broadened the tax base, improved institutional processes, and made fiscal tools more in line with environmental goals.

These findings suggest that the effectiveness of carbon taxation depends not only on tax rates but also on the policies, governance framework, and institutional context in which it is implemented. The study demonstrates that data-driven, multi-criteria frameworks such as WENSLO-MCRAT can assist developing nations aiming for low-carbon expansion by effectively linking empirical assessments to policy formulation.

This study has some problems, even though the WENSLO–MCRAT framework is strong. To begin with, the analysis is based on static, cross-sectional data, which means that these data can't show how the effectiveness of a policy changes over time or when the economy changes. Second, even though the criteria for the evaluation were based on research and relevance, they don't cover everything that needs to be looked at to see how well the carbon price works. For example, important factors like how easy it is to implement, how likely it is to get political support, or how well institutions can handle it are not looked at closely enough. The model also assumes that policymakers in each country are fair and consistent. However, this assumption may not always be true in real life, especially in developing countries where the government is not always working well together. Finally, the WENSLO method provides an impartial means of distributing weight; however, its lack of expert involvement may result in the exclusion of significant nuances that a hybrid approach could offer.

Subsequent research may expand the scope of this study by incorporating dynamic variables, including the progression of the carbon market, the structure of subsidy systems, and technological readiness into the analysis. Longitudinal studies evaluating the effectiveness of carbon pricing over time could significantly enhance the literature by providing in-depth insights into the consequences of policy. Moreover, integrating qualitative indicators such as institutional capacity, public acceptance, and governance quality into the analytical framework could enhance the methodological rigor of the study and support the development of more comprehensive and effective policy recommendations.

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EVALUATING THE IMPACT OF ESG AND DECARBONIZATION METRICS ON STOCK PRICE PREDICTION

ESG ve Karbon Azaltma Metriklerinin Hisse Senedi Fiyat Tahmini Üzerindeki Etkisinin Değerlendirilmesi

Çiğdem YERLİ* 

Abstract

This study investigates the effectiveness of incorporating sustainability metrics, specifically ESG scores and corporate decarbonization targets, into stock price prediction models using LSTM neural networks. The aim is to assess whether these non-financial indicators enhance predictive accuracy across different sectors. The analysis focuses on five BIST 100 companies from diverse industries, using data spanning from 1 January 2020 to 19 March 2025. Three model configurations were tested: one based solely on historical stock prices, one with added ESG scores, and another with decarbonization data. The data were preprocessed using normalization techniques and split into training and testing sets to ensure robust model performance. Results were evaluated using MAE, MSE, and RMSE. Findings reveal that sustainability metrics improved prediction accuracy primarily in emission-intensive sectors like aviation (THYAO) and oil refining (TUPRS), while offering limited or even negative impact in others, such as defense (ASELS). Surprisingly, steel producer EREGL showed only modest gains despite expectations of higher sensitivity. Overall, the study shows that the influence of sustainability metrics on financial forecasting varies by sector. It underscores the importance of tailoring input features to fit the unique dynamics of each industry.

Anahtar

Kelimeler:

ESG,
Decarbonization,
Financial
Forecast, LSTM

JEL Kodları:

C45, C53, Q56

Öz

Bu çalışma, sürdürülebilirlik metriklerinin, özellikle ESG puanları ve kurumsal karbon azaltım hedeflerinin, LSTM sinir ağıları kullanılarak yapılan hisse senedi fiyat tahmin modellerine entegre edilmesinin etkinliğini incelemektedir. Amaç, bu finansal olmayan göstergelerin farklı sektörlerde tahmin doğruluğunu artırıp artırmadığını değerlendirmektir. Analiz, 1 Ocak 2020 ile 19 Mart 2025 tarihleri arasındaki veriler kullanılarak, çeşitli sektörlerden beş BIST 100 şirketine odaklanmaktadır. Üç farklı model yapısı test edilmiştir: yalnızca geçmiş hisse senedi fiyatlarına dayalı bir model, ESG puanlarının eklendiği bir model ve karbon azaltım verilerini içeren model. Veriler, normalizasyon teknikleriyle ön işleme tabi tutulmuş ve güçlü bir model performansı sağlamak amacıyla eğitim ve test setlerine ayrılmıştır. Sonuçlar, MAE, MSE ve RMSE ölçütleri kullanılarak değerlendirilmiştir. Bulgular, sürdürülebilirlik metriklerinin özellikle havacılık (THYAO) ve petrol rafinajı (TUPRS) gibi emisyon yoğun sektörlerde tahmin doğruluğunu artırdığını, savunma sanayi (ASELS) gibi diğer bazı sektörlerde ise sınırlı veya olumsuz etkiler gösterdiğini ortaya koymaktadır. Beklentilere rağmen, çelik üreticisi EREGL yalnızca sınırlı düzeyde iyileşme göstermiştir. Genel olarak, çalışma sürdürülebilirlik ölçümlerinin finansal tahmin üzerindeki etkisinin sektöre göre değiştiğini göstermektedir. Her sektörün benzersiz dinamiklerine uyacak şekilde girdi özelliklerinin uyarlanması önemi vurgulamaktadır.

Keywords:

ESG, Karbon
Azaltım, Finansal
Tahmin, LSTM

JEL Codes:

C45, C53, Q56

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1. Introduction

Sustainability has become an important global priority, reshaping how businesses approach long-term strategies. Growing emphasis on sustainable development has led companies to integrate Environmental, Social, and Governance (ESG) criteria into their performance evaluations (Egorova et al., 2022; Lee et al., 2023). These metrics help assess a firm’s environmental impact, ethical standards, and leadership quality, offering a clear framework to measure its commitment to sustainable operations (Lee et al., 2024). Companies that adopt environmentally friendly practices, prioritize social welfare, and maintain transparent governance tend to earn higher investor trust. Studies suggest that high ESG performance frequently correlates with higher stock valuations, as stakeholders view these initiatives as reducing risk and supporting long-term profitability (Aybars et al., 2019). This relationship motivates companies to enhance their sustainability efforts, fostering closer collaboration between businesses and investors while advancing shared economic and ethical objectives (In et al., 2019).

Sustainability and ESG metrics are increasingly influencing investor behavior in financial analysis. This change highlights the importance of incorporating ESG factors into evaluation models, effectively linking responsible corporate actions with long-term investment strategies. Employing ESG indices to forecast benchmarks like the S&P 500 represents a new approach that acknowledges ESG considerations in guiding investment decisions (Alareeni and Hamdan, 2020). The increasing interest in how ESG performance influences equity valuation highlights the growing significance of ESG metrics in today’s financial markets (Kiesel and Lücke, 2019; Scatigna et al., 2021).

The financial sector is key to this transition, as it incorporates ESG factors into its investment decision-making processes. This approach supports ongoing investments in sustainable projects and initiatives (European Commission, 2025). According to the OECD, integrating ESG factors into financial evaluations is increasingly shaped by urgent global challenges, including climate change, social inequality, corporate governance standards, and ethical business practices (Boffo and Patalano, 2020). ESG indicators play a crucial role, and their integration offers significant potential. This research adopts a comprehensive analytical approach to thoroughly examine the synergy created by combining these factors.

In recent years, CO² emission targets and corporate awareness of carbon footprints have emerged as key topics in academic research, reflecting a broader shift toward environmental accountability. These indicators are now central to evaluating corporate sustainability, alongside other environmental metrics. At the policy level, governments are taking a more active role in regulating emissions. The European Union, for instance, has introduced measures such as the EU Green Deal and the "Fit for 55" initiative, both designed to reduce emissions from major corporations through a mix of regulation and taxation. In the USA, legislation like the Clean Air Act enforces similar standards. As a result, environmental compliance is no longer optional but a binding obligation for firms. In this evolving regulatory landscape, understanding the influence of decarbonization targets on market behavior is becoming increasingly important. Investigating the role of emission goals in financial performance can help bridge the gap between sustainable investment strategies and market outcomes, supporting more informed and responsible investment decisions.

The emergence of machine learning has significantly improved the forecasting of financial markets. An extensive body of literature highlights machine learning’s superior predictive

capabilities compared to traditional forecasting methods. By incorporating historical stock data and environmental metrics, machine learning models may facilitate accurate predictions of future stock price movements. Consequently, investors can strategically allocate capital to promote responsible business practices, fostering a socially and environmentally sustainable investment landscape.

Given the increasing importance of ESG factors in investment decision-making and corporate strategy, a substantial body of literature has emerged examining the relationship between ESG performance and firm financial outcomes. However, the findings remain fragmented and inconclusive. A number of studies suggest a positive correlation, indicating that strong ESG performance contributes to improved firm value and financial performance (Yoon et al., 2018; Deng and Cheng, 2019; Berg et al., 2022; Lapinskienė et al., 2023). In contrast, other researchers report a negative relationship, implying that ESG investments may divert resources from core profit-generating activities (Brammer et al., 2006; Di Tommaso and Thornton, 2020; Luo, 2022). Still, some studies find no statistically significant correlation between ESG metrics and corporate financial performance, suggesting the effects may be context-dependent or influenced by methodological choices (Halbritter and Dorfleitner, 2015; La Torre et al., 2020).

In addition to these conflicting findings, a critical gap exists in the geographical scope of existing research. Most empirical studies have concentrated on firms in developed markets, where ESG disclosure standards are more established and regulatory frameworks are more consistent (Brammer et al., 2006; Di Tommaso and Thornton, 2020; Luo, 2022; Berg et al., 2022; Lapinskienė et al., 2023). In contrast, relatively few studies have examined ESG performance in emerging economies, where institutional environments, investor behavior, and ESG implementation practices can differ significantly (Yoon et al., 2018; Deng and Cheng, 2019). This imbalance limits the generalizability of existing findings and overlooks important regional dynamics.

This study directly addresses a critical gap in existing literature by evaluating the predictive value of ESG metrics, particularly corporate decarbonization indicators, within the context of an emerging market. To this end, we propose a novel methodological approach that integrates these sustainability variables into advanced machine learning frameworks. Specifically, we utilize Long Short-Term Memory (LSTM) neural networks, which are well-suited for modeling the nonlinearities and temporal dependencies characteristic of financial time series data. Our empirical setting is the Turkish stock market, which offers a compelling case study due to Turkey's status as a prominent emerging economy undergoing significant transitions in both its sustainability practices and capital market development.

The primary aim of the study is to assess whether the incorporation of environmental indicators improves the forecasting performance of LSTM-based trading models. In doing so, we contribute to the methodological advancement of ESG-based financial modeling and provide practical insights for investors and finance professionals seeking to integrate sustainability considerations into quantitative trading strategies. Furthermore, we examine which stocks exhibit the greatest sensitivity to ESG-related data, offering a nuanced understanding of how sustainability information may influence financial market behavior in emerging economies.

The remainder of this paper is structured as follows. First, a comprehensive literature review is presented. Next, the data and methodology employed are described in detail, followed

by an overview of the proposed LSTM model. The subsequent sections provide an analysis of the results, concluding with a summary of the study's primary findings and contributions.

2. Literature Review

2.1. A Review of Predicting the Stock Price with LSTM

The advantages of LSTM networks for forecasting financial time series data have been extensively documented in academic research. Chen et al. (2015) applied LSTM to predict stock returns in the Chinese market. They segmented historical data into 30-day sequences, each including ten learning features, and found that LSTM significantly improved forecasting accuracy from 14.3% (baseline) to 27.2%, clearly outperforming random prediction models. Similarly, Fischer and Krauss (2018) assessed LSTM's performance in classifying directional movements of S&P 500 stocks between 1992 and 2015. They concluded that LSTM significantly surpassed traditional methods such as logistic regression, random forests, and conventional deep neural networks. In a comparative study, Yu and Yan (2020) integrated LSTM with phase-space reconstruction techniques, forecasting prices of multiple indices, including the S&P 500, DJIA, and Nikkei 225. Their results demonstrated the clear superiority of LSTM over other methods like Multilayer Perceptron, Support Vector Regression, and ARIMA, particularly highlighting strong performance with the S&P 500 dataset. In addition, Karmiani et al. (2019) evaluated various predictive algorithms, LSTM, SVM, Backpropagation, and Kalman filters, on stock data from nine companies. Their findings confirmed that LSTM achieved the highest accuracy and lowest variance among all tested methods. Further emphasizing LSTM's effectiveness, Niu et al. (2020) conducted comparative analyses on daily closing price predictions across indices such as the Hang Seng, S&P 500, FTSE, and Nasdaq between 2010 and 2019. They observed consistently lower root mean square errors (RMSE) for LSTM, particularly noting exceptional performance in predicting Nasdaq index prices. Similarly, Xiao et al. (2022) examined daily stock price forecasts across 50 stocks from 2010 to 2018. Their study reaffirmed LSTM's predictive advantage over ARIMA, attributing its superior performance to the model's memory capabilities and its ability to capture intricate temporal dependencies. However, they also noted considerable variation in LSTM performance across different stocks, suggesting that forecasting accuracy might depend on stock-specific characteristics. Furthermore, Karaboga et al. (2024) evaluated LSTM and Random Forest (RF) models to predict daily closing prices of Turkcell's stock, using data from both BIST and NYSE (2010–2023). Their results clearly demonstrated that LSTM achieved better forecasting accuracy than RF, particularly for the NYSE dataset. Finally, Sönmez and Arslan (2024) assessed LSTM's predictive ability for the BIST-100 and Frankfurt Stock Exchange's DAX index, using various volatility indices as input variables. Covering data from January 2012 to June 2024, their study validated LSTM's strength in capturing long-term temporal relationships and confirmed its strong forecasting performance.

2.2. The Review of ESG Impact on the Stock Performance

There is growing academic interest in how ESG factors influence stock prices, as more investors consider sustainability in their decision-making. Several studies have examined how ESG performance impacts stock returns and firm valuation. For instance, Cek and Eyupoglu (2020) assess the impact of ESG performance on the economic performance of S&P 500 firms

using data from 2010 to 2015 and applying structural equation modeling and regression analysis. They find a significant overall relationship between ESG and economic performance, with social and governance factors showing consistent positive effects. Environmental performance, however, does not exhibit a significant impact. Yoon et al. (2018) applied Ohlson's valuation model to 705 Korean firms from 2010 to 2015. They found a positive relationship between corporate social responsibility and share prices, especially in industries with high environmental or social sensitivity. Similarly, Deng and Cheng (2019) analyzed data from Chinese firms between 2015 and 2019 using panel regression. Their results showed that higher ESG ratings were associated with better stock returns. They also noted that this effect was stronger for private companies compared to public ones. Furthermore, Buallay (2019) examined 235 banks from 2007 to 2016 and reported that ESG ratings had a positive impact on firm market value. In the MENA region, Al-Hiyari and Kolsi (2021) conducted a study on 439 companies across 10 countries during 2013–2019. Their findings also showed a positive link between ESG performance and market value. Engelhardt et al. (2021) investigate the relationship between ESG ratings and stock performance during the COVID-19 crisis. Analyzing a sample of 1,452 firms across 16 European countries, they find that companies with high ESG ratings experienced higher abnormal returns and lower stock volatility, suggesting better performance compared to firms with low CSR ratings. Another study by Berg et al. (2022) looked at companies in North America, Europe, and Japan between 2014 and 2020. They found that higher ESG scores were associated with stronger expected returns. Similarly, Lapinskienė et al. (2023) analyzed 500 large U.S. companies and 600 EU firms over the period 2015–2020. Their research highlighted that stock price movements were partly influenced by environmental initiatives, emphasizing the growing importance of the “E” in ESG. Ateş et. al (2022) examine the comparative performance of sustainable-themed funds against traditional funds and indices in Turkey, aiming to determine whether sustainability-focused investments outperform conventional alternatives. Using daily data from 2019 to 2022, they analyze the BIST Sustainable Index (XUSRD) as the benchmark for sustainable funds and the BIST100 Index (XU100) as the benchmark for traditional funds. The Capital Asset Pricing Model (CAPM) is applied to calculate portfolio returns and systematic risks. The results show that sustainable-themed funds demonstrate stronger performance than their traditional counterparts and the broader market indices. More recently, Gül and Altuntaş (2024) investigated 347 companies from both advanced and emerging markets between 2010 and 2022. Their study confirmed a statistically significant positive effect of ESG ratings and return on assets on stock performance, with especially strong results observed in emerging markets.

In contrast to studies demonstrating positive impacts of ESG on financial performance, some researchers report neutral or even negative relationships. Brammer et al. (2006) investigate the relationship between corporate social performance and stock returns in the United Kingdom. Rather than relying on an aggregate measure, they adopt a disaggregated approach, analyzing specific dimensions of social performance, including environmental practices, employment policies, and community engagement. The findings reveal a negative association between composite social performance scores and stock returns. The authors attribute this underperformance primarily to firms' strong environmental initiatives and, to a lesser extent, their community-related activities. Moreover, they report that portfolios composed of the least socially responsible firms yield significant abnormal returns. The authors examine the influence of ESG scores on the risk-taking behavior and firm value of European banks. Their analysis reveals that higher ESG scores are linked to a modest decrease in risk-taking. Also, the authors also find that

elevated ESG scores are associated with a decline in bank value. They conclude that ESG initiatives may divert scarce resources away from more value-enhancing investments. Halbritter and Dorfleitner (2015), for instance, examined the U.S. market and found no statistically significant relationship between ESG scores and stock market returns. Their analysis revealed no meaningful differences between high- and low-ESG portfolios. Similarly, La Torre et al. (2020) investigated 46 public companies listed on the Eurostoxx50 from 2010 to 2018 using panel analysis and multiple linear regression. Their findings indicated no significant impact of ESG ratings on corporate financial performance. Luo (2022) studied UK-listed stocks between 2003 and 2020 and presented evidence that firms with lower ESG scores could achieve higher returns. Luo's analysis supports a risk–return trade-off hypothesis, suggesting investors require greater compensation when investing in firms with weaker ESG profiles. Gavrilakis and Floros (2023), analyzing large companies across six European countries over the period 2010–2020, similarly reported that investing in firms with high ESG ratings typically did not lead investors to sacrifice returns. These findings highlight ongoing debates within the literature regarding the precise influence of ESG factors on financial performance.

The abovementioned literature presents conflicting evidence regarding the impact of ESG scores on stock performance. Moreover, most existing research focuses on developed markets, with emerging economies remaining underrepresented. These issues highlight a research gap that this study seeks to address using data from Turkey. Specifically, the study investigates the effect of ESG on BIST-listed stocks, representing an emerging market, through a machine learning approach. The following section provides a detailed description of the dataset and methodology.

3. Data and Methodology

3.1. Data

This study examines the environmental performance of five companies listed on the Borsa Istanbul (BIST) index, using data sourced from MSCI ESG ratings. These firms were selected based on their availability of the MSCI ESG ratings, which have consistently published ESG scores since 2020. The dataset comprises daily stock prices from 1st of January 2020, to 19th of March 2025, offering five ESG ratings to each company. In addition to ESG scores, the study incorporates information on each firm's carbon reduction strategies, obtained from the MSCI ESG Ratings and Climate Research Tool. The selected companies operate across different industries, enabling a cross-sector comparison of environmental performance and its potential influence on stock prices. The use of MSCI data ensures transparency and reliability, as all ESG scores and climate-related disclosures are publicly accessible via [msci.com](https://www.msci.com).

Table 1 demonstrates five selected companies listed on the Borsa Istanbul (BIST) index and presents alongside their industries, ESG correlations, and key reasons for their specific ESG risk levels. These companies include Aselsan (ASELS) from defence and aerospace, Ereğli Demir Çelik (EREGL) from steel and metal production, Turkcell (TCELL) from telecommunications, Turkish Airlines (THYAO) from aviation, and Tüpraş (TUPRS) from oil and gas refining. The table also presents each company's ESG correlation levels and the rationale behind these classifications. Companies from heavily polluting industries, such as steel production, aviation, and oil refining, demonstrate a high correlation with ESG issues due to their significant carbon footprints, environmental impacts, and pressures to decarbonize. Turkcell shows a medium-high

ESG correlation, primarily influenced by factors like data privacy, cybersecurity, energy efficiency, and governance practices. In contrast, defence-sector firms like Aselsan typically have medium ESG correlations, mainly influenced by governance risks, ethical concerns, and regulatory scrutiny rather than direct environmental impacts. Thus, analysing this diverse group of companies allows for a detailed exploration of how ESG considerations vary across sectors and how different industries respond to environmental and sustainability pressures.

Table 1. Selected BIST Companies and Their ESG Relevance by Sector

Ticker	Company	Sector	ESG Correlation	Reason
ASELS	Aselsan	Defense & Aerospace	Medium	Defense companies face governance risks, ethical concerns, and regulatory scrutiny but are not always ESG-friendly.
EREGL	Ereğli Demir Çelik	Steel & Metal Production	High	The steel industry is highly polluting and under pressure to shift toward green steel and decarbonization.
TCELL	Turkcell	Telecommunications	Medium	Telecom companies are evaluated on data privacy, cybersecurity, energy efficiency, and governance practices.
THYAO	Turkish Airlines	Aviation	High	Airlines have high carbon footprints, and ESG ratings depend on their sustainability initiatives (e.g., sustainable aviation fuel, carbon offsets).
TUPRS	Tüpraş	Oil & Gas Refining	High	Fossil fuel companies are ESG-sensitive due to emissions, environmental risks, and transition pressure toward cleaner energy sources.

Following the approach of Ruan and Liu (2021), the qualitative MSCI ESG ratings were converted into numerical values to facilitate quantitative analysis. As shown in Table 2, ratings ranging from 'CCC' to 'AAA' were assigned scores from 1 to 7, respectively. This numerical representation allows for consistent integration of ESG data into the forecasting model.

Table 2. MSCI ESG Ratings and Corresponding Scores

ESG Rating	AAA	AA	A	BBB	BB	B	CCC
Assigned ESG Score	7	6	5	4	3	2	1

Similarly, decarbonization efforts were quantified using a scoring framework adapted from Le Guenedal et al. (2025) and In et al. (2019). Table 3 outlines the classification of carbon reduction targets into six levels, with corresponding scores ranging from 0 (no target) to 100 (net-zero target with detailed plans and full disclosures). This scoring system captures the degree of commitment and specificity in a firm's climate strategy.

Table 3. MSCI Carbon Emission Targets and Assigned Scores

Level	Description	Example	Assigned Score
0	No target	No stated reduction goal	0
1	Vague, unquantified target	“We aim to reduce emissions someday”	20
2	Quantified but not time-bound	“We aim to cut emissions by 30%”	40
3	Medium-term, quantified, no science-based validation	“50% by 2030, but no SBTi alignment”	60
4	Near-term, science-based or SBTi-approved target	“SBTi 1.5°C-aligned by 2030”	80
5	Net-zero, detailed transition plan, transparent disclosures	Net-zero by 2050 + scope 3 + roadmap	100

Figure 1 demonstrates the letter scores for the five selected BIST-listed companies—Aselsan (Asels), Ereğli Demir ve Çelik (Ereğl), Turkcell (Tcell), Turkish Airlines (Thyao), and Tüpraş (Tuprs)—over the 2020–2024 period. These scores reflect variations in environmental performance across time and sectors. Table 4 presents the corresponding scalar scores for these letter scores given in Figure 1.

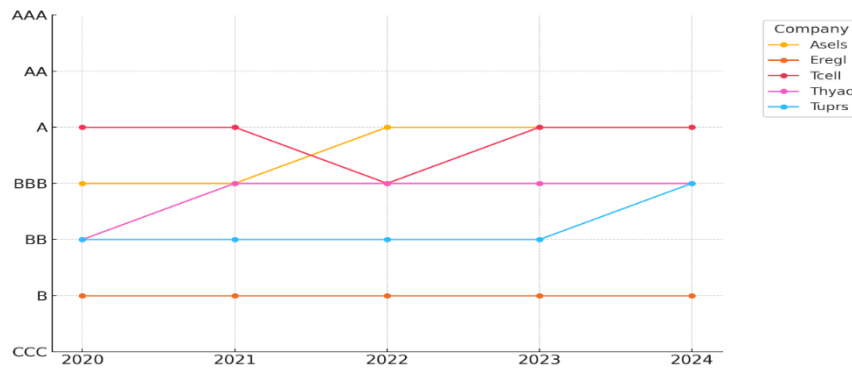


Figure 1. ESG Scores of the Selected Companies 2020-2024

Table 4. Selected Companies ESG Scores

Year	Asels	Ereğl	Tcell	Thyao	Tuprs
2020	4	2	5	3	3
2021	4	2	5	4	3
2022	5	2	4	4	3
2023	5	2	5	4	3
2024	5	2	5	4	4

Table 5 summarizes the decarbonization scores assigned to each company based on the most recent available data. The scores reveal notable differences in the ambition and clarity of emissions targets, providing a foundation for evaluating the relationship between decarbonization efforts and stock market performance.

Table 5. Selected Companies Decarbonization Scores

	Asels	Eregl	Tcell	Thyao	Tuprs
Level	4	1	4	3	2
Score	80	20	80	60	40

3.2. Methodology

In this study, an LSTM model for stock price prediction is tested over data set belonging to 5 different BIST 100 companies from various industries. In this case, it will be a parallel of performing three modeling treatments on the same company data for the same period. The application is written using Python.

The first model is simply a baseline that uses only historical stock price data, mimicking a conventional financial forecasting model—one that does not incorporate greenhouse gas emissions or other sustainability-related input. The second model builds on this baseline by including ESG scores, allowing us to measure their impact on the predictive accuracy of the model. The third model includes corporate decarbonization targets as additional inputs, allowing you to see how climate commitments impact price predictions.

The methodology follows a structured methodology consisting of five main steps to evaluate the performance of an LSTM model for stock price prediction. The methodology involves data processing, model construction, and performance evaluation using data from five BIST 100 companies across various industries.

Step 1: Editing the Data

The first step involves collecting and reviewing financial and environmental data. Five selected BIST 100 companies' historical stock prices and ESG scores, and corporate decarbonization targets are obtained. The datasets are synchronized and standardized to be uniform, and timestamps are aligned among all features to enable synchronized input to the LSTM. This step also standardizes the datasets from different sources and makes them structurally and in terms of content uniform.

Step 2: Preprocessing of the Data

All input features are normalized while preprocessing by utilizing the MinMaxScaler from the scikit-learn library. The stock prices and other features are normalized between 0 and 1 and are made ready to train the model. ESG scores are normalized between 1 and 7 to prevent the model from becoming idle due to zero inputs. Normalization supports faster and improved learning and convergence of the model. The inputs are also reshaped to maintain the dimensions as per the requirements of recurrent neural networks.

Step 3: Training and Test Data Sets

To ensure robust generalization and minimize the risk of overfitting, the dataset is partitioned chronologically into training, validation, and testing subsets. This temporal ordering preserves the natural autocorrelation structure of time-series data and prevents data leakage across modeling stages. At the firm level, an 80–20 chronological split is implemented: the earliest 80% of observations form the model development window, while the most recent 20% serve as an out-of-sample test set. Within the development window, the final 10% is reserved as a validation set

for hyperparameter tuning, following an expanding window procedure. This results in an effective 72/8/20 split for training, validation, and testing, respectively.

Step 4: The LSTM Algorithm

The LSTM model was developed using TensorFlow's Keras Sequential API, with Dense layers added to support output processing. Several versions of the model were tested to evaluate performance under different input conditions. The first was a baseline model that relied solely on historical closing price data. Another version incorporated five ESG score inputs to capture sustainability-related factors. Finally, a third model included decarbonization target inputs to assess the impact of climate-focused goals on performance.

The model architecture includes special LSTM units that regulate data flow through three primary gates: the input gate, the forget gate, and the output gate (Oancea and Simionescu, 2024). These gates utilize sigmoid activation functions to manage memory updates and retain long-term patterns. The input gate is responsible for determining how much of the new input should be stored in the cell state. The forget gate decides which parts of the previous cell state should be removed. The output gate controls the amount of information from the cell state that will be passed to the next hidden state. The cell structure is presented in Figure 1.

Mathematically, the gates operate as follows:

$$\text{Input gate: } i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (1)$$

$$\text{Forget gate: } f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

$$\text{Output gate: } o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

A sequence length of 64 was selected after testing various lengths (10, 32, 64, 100, 134), as it provided the most reliable performance. The Adam optimizer was employed for training, offering adaptive learning capabilities suitable for time-series modeling. The model architecture is presented in Figures 2 and 3.

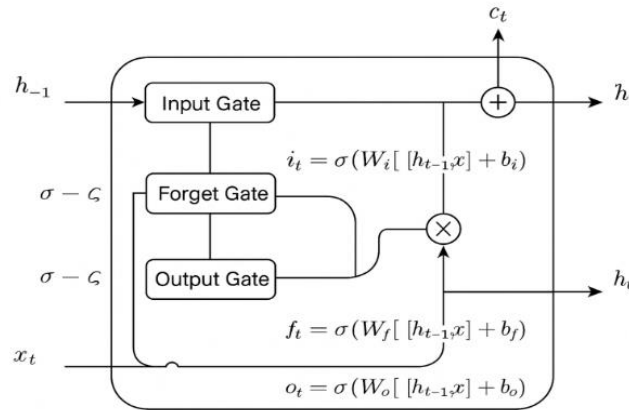


Figure 2. A LSTM Cell

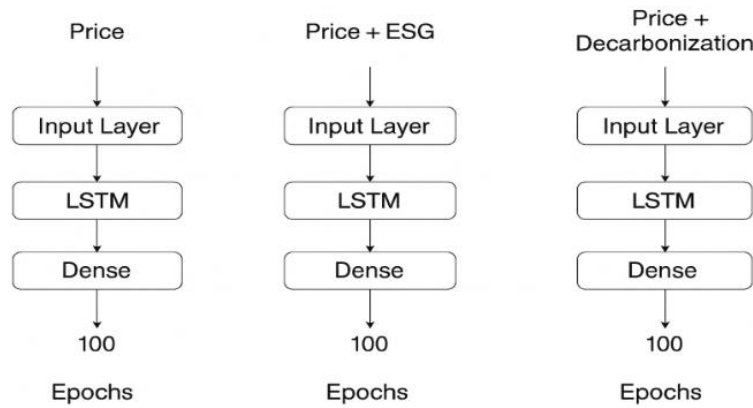


Figure 3. The Model Architecture

Hyperparameter tuning followed a structured, coarse-to-fine search protocol, employing validation splits and an expanding window evaluation approach to maintain temporal integrity. The optimal number of LSTM units was established at 50, providing adequate representational capacity without over-parameterization issues encountered with higher unit counts. Batch size was set to 32, optimizing gradient stability and efficiency, as smaller batches increased gradient noise, and larger batches slightly degraded validation accuracy. The Adam optimizer was chosen due to its effective adaptive learning rate for non-stationary data sequences, offering faster and more stable convergence compared to alternative methods. An initial learning rate of 0.001, determined via grid search 10^{-2} , 10^{-3} , 10^{-4} ensured smooth loss progression without excessive oscillation. Regularization involved applying a dropout rate of 0.2 to LSTM outputs before the Dense layers, effectively mitigating overfitting without significantly compromising training performance. Higher dropout rates (≥ 0.3) impaired learning, while lower rates (< 0.2) insufficiently controlled variance.

Step 5: Performing the Estimation Process and Measuring Its Accuracy

The estimation process involved training each version of the LSTM model for 100 epochs, which was identified as the optimal count, balancing training time and performance. During this process, the model made predictions for the next five trading days using the preceding 64 days as input. Performance was measured using error analysis, focusing on how the inclusion of additional features (ESG scores and decarbonization targets) affected prediction accuracy. After training, the normalized outputs were converted back to actual stock prices using inverse transformation, enabling the interpretability of the results. Through this iterative learning and evaluation, the model refined its internal parameters to improve predictive performance over time.

3.3. Error Measurements Metrics

Three widely used error measurement metrics, namely Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), are used to evaluate the predictive performance of the LSTM models (Botunac et al., 2024). These metrics provide complementary insights into model accuracy. MAE measures the average magnitude of the prediction errors without considering their direction, offering a straightforward interpretation of the model's accuracy. MSE, by squaring the errors, penalizes larger deviations more heavily, making it

sensitive to outliers. RMSE, as the square root of MSE, retains the same unit as the target variable and offers a balanced view by combining the benefits of both MAE and MSE. Together, these metrics enable a comprehensive assessment of the model's forecasting capability. The metrics are given as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (6)$$

In these formulas, y_i represents the actual value, $\hat{y}_i$ is the predicted value, and n is the total number of predictions. These metrics together provide a comprehensive view of model accuracy and help identify the most effective input combinations.

4. Results and Discussion

This part explores the predictive capability of the LSTM model in forecasting stock prices under three different data configurations: (1) using historical price data alone, (2) integrating historical prices with ESG scores, and (3) combining historical prices with companies' decarbonization targets. The goal is to assess whether the inclusion of sustainability-related information enhances the model's forecasting performance, and if so, which stocks are most sensitive to these additional data sources. In addition to time-series prediction plots, the study includes histogram and Kernel Density Estimation (KDE) plots for each stock across the three cases. These plots provide a visual comparison between the distribution of actual prices and the distribution of LSTM-predicted prices, highlighting how well the model captures the statistical structure and variance in stock price behavior. Also, MAE, MSE, and RMSE error measurements are provided for all cases.

In the first case, the LSTM model was trained solely on historical price data. The results serve as a benchmark for evaluating the effects of incorporating ESG and decarbonization variables. In Figure 4, visually, the LSTM model exhibits strong predictive performance, closely following the trends and short-term fluctuations of the actual price series. The results are also supported by the histograms and KDE in Figure 5, which indicate a reasonably close match between actual and predicted price distributions.

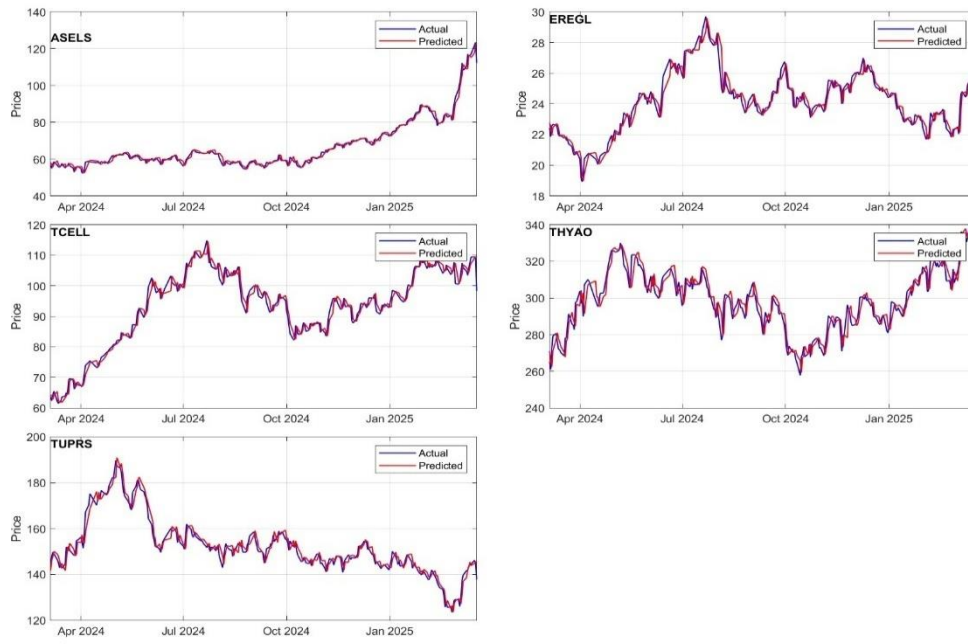


Figure 4. Actual Prices Versus Predicted Prices – First Case: Price Only

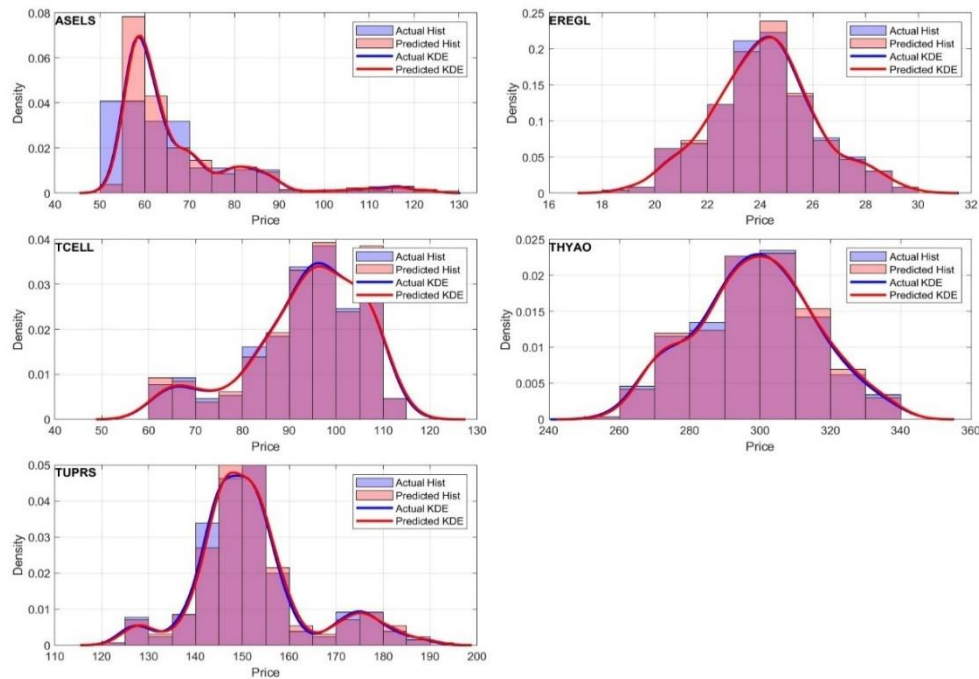


Figure 5. Histograms and KDEs of Actual Prices Versus Predicted Prices – First Case: Price Only

In Table 6, the results indicate that while the model generally tracks the stock price patterns closely, its accuracy varies significantly across companies. EREGL exhibits the lowest RMSE at 0.5177, indicating a relatively stable and predictable price trajectory, which the LSTM model captures effectively. In contrast, THYAO shows the highest RMSE at 5.7448.

Table 6. Error Metrics - First Case: Price

Stock	MAE	MSE	RMSE
ASELS	1.2592	3.1893	1.7859
EREGL	0.37863	0.26797	0.51766
TCELL	1.5547	4.3256	2.0798
THYAO	4.5348	33.003	5.7448
TUPRS	2.1846	7.3023	2.7023

In the second case, ESG scores are added as an additional feature alongside historical price. Visually, in Figure 6, it exhibits strong predictive performance, closely following the trends and short-term fluctuations of the actual price series. The inclusion of ESG data results in modest but consistent improvements in model performance across all five companies. The RMSE dropped slightly for every stock, suggesting that ESG data may carry supplementary explanatory power beyond price history.

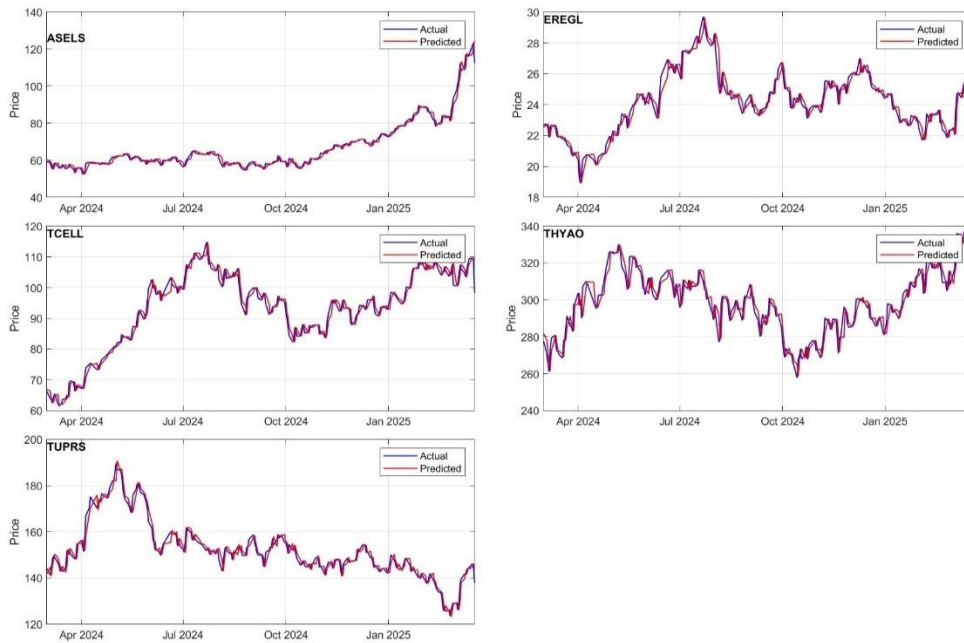


Figure 6. Actual Prices Versus Predicted Prices – Second Case: Price + ESG

In Figure 7, with the inclusion of ESG scores, the predicted histograms show improved alignment with the actual price distributions for most stocks. For instance, ASELS now exhibits a KDE curve that more accurately captures the steep peak in the lower price range. This change supports the idea that ESG scores provide additional explanatory power, helping the model better understand the concentration of values around certain price levels. Similarly, THYAO's predicted distribution more closely resembles the actual one, particularly in terms of symmetry and spread. The tail behavior for TUPRS is also better captured in this configuration, reflecting improved prediction of rare or less frequent price levels.

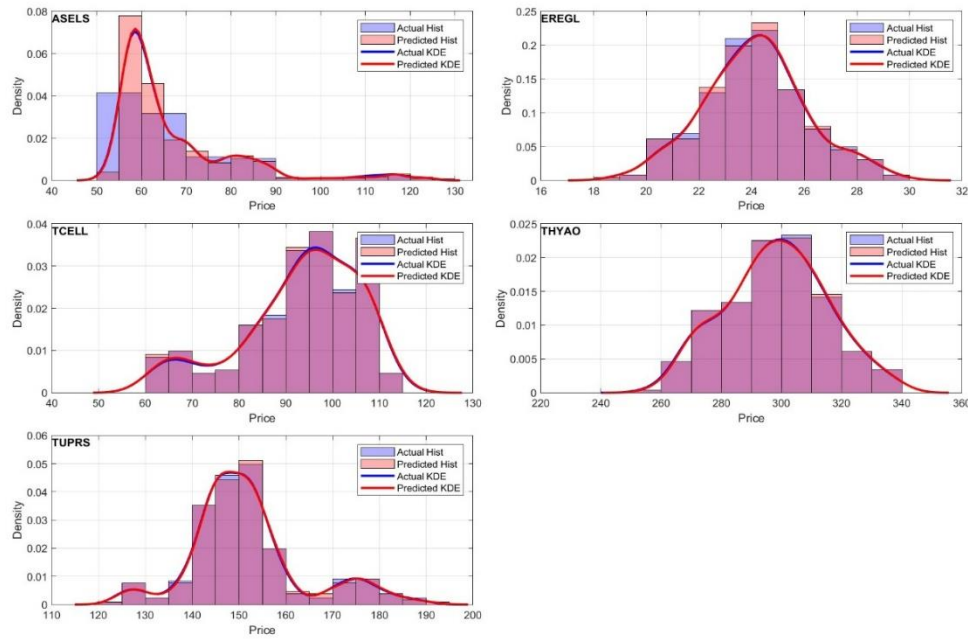


Figure 7. Histograms and KDEs of Actual Prices Versus Predicted Prices – Second Case: Price + ESG

As seen from Table 6 and Table 7, THYAO demonstrates a substantial improvement with a reduction in RMSE from 5.7448 to 5.5980. This is significant, as THYAO operates in the aviation sector—an industry that is highly exposed to ESG-related risks, including carbon emissions, fuel efficiency, and regulatory pressures. The improvement suggests that market participants may be incorporating ESG information into their pricing decisions for such firms, and the LSTM model benefits from having this context. The other companies show smaller but still positive gains. Contrary to the expectations that EREGL and TUPRS, both in carbon-intensive sectors, should be affected by the ESG score more, they did not. For instance, ASELS sees a minor drop in RMSE to 1.7789, while TUPRS decreases to 2.6414. The consistency of these improvements across all stocks suggests that ESG scores provide valuable supplementary information that captures qualitative or intangible aspects of firm performance not evident in price data alone. Although the magnitude of performance enhancement is modest, it is statistically meaningful given the model's complexity and the noise inherent in financial markets.

Table 7. Error Metrics - Second Case: Price + ESG

Stock	MAE	MSE	RMSE
ASELS	1.2683	3.1644	1.7789
EREGL	0.37166	0.26178	0.51165
TCELL	1.5336	4.1817	2.0449
THYAO	4.3652	31.337	5.598
TUPRS	2.133	6.9771	2.6414

In the third scenario, decarbonization targets are used instead of ESG scores, and actual versus predictive stock prices are presented in Figure 8. The model again shows high accuracy, closely following the actual price's trends and movements, similar to Figure 6. Importantly, leveraging decarbonization data provided small but reliable performance gains for all five

companies. While the visual difference between the predicted prices in Figure 6 and Figure 8 is subtle, Table 8 quantifies the performance improvement.

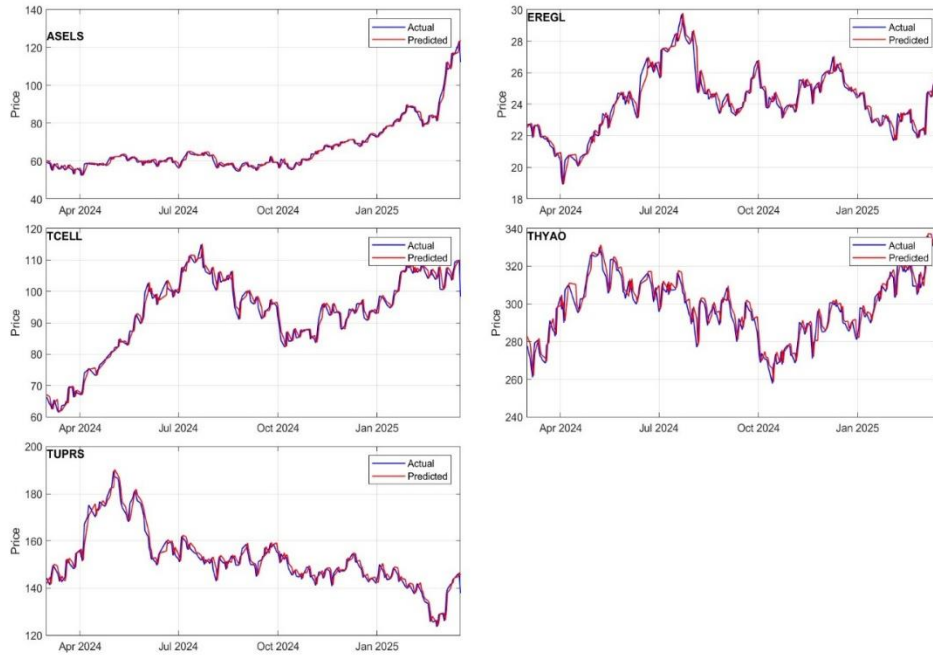


Figure 8. Actual Prices Versus Predicted Prices – Third Case: Price + Decarbonization

In Figure 9, where decarbonization targets are included, the histogram plots reveal more varied results across stocks. For some firms—particularly THYAO and TUPRS—the predicted distributions improve further, closely aligning with the actual KDE curves in both the center and the tails. This suggests that carbon-related disclosures enhance the model's ability to capture price behavior in industries more exposed to environmental regulations and carbon pricing. In contrast, the predictions for ASELS show a slight mismatch. The predicted KDE curve becomes wider and less sharp, indicating that decarbonization data may add noise rather than useful signals for this stock, likely due to its lower sensitivity to carbon-related factors. TCELL presents another interesting case. Although the predicted and actual distributions generally align well, the inclusion of decarbonization targets introduces mild overfitting in the central region, where the model produces an overly smooth curve that misses the slightly multimodal shape of the actual data. This may suggest that for telecom companies like TCELL, ESG factors are more informative for stock prediction than specific carbon metrics.

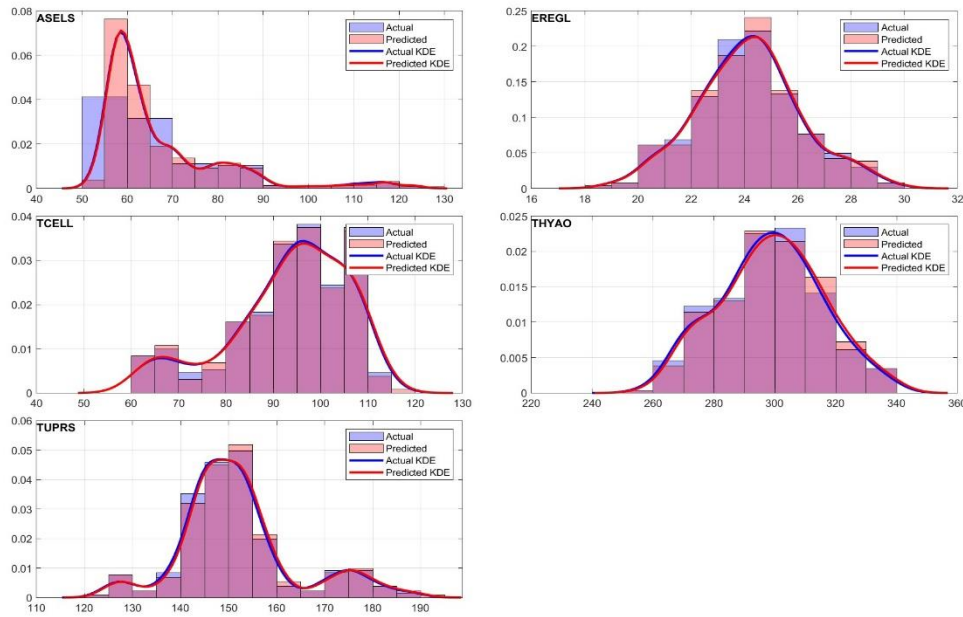


Figure 9. Histograms and KDEs of Actual Prices Versus Predicted Prices – Third Case: Price + Decarbonization

Table 8 demonstrates the performance results of the third case. Based on the results in Table 8, THYAO continues to show strong sensitivity to sustainability-related data, with its RMSE dropping from 5.7448 in the baseline model to 5.5199 in the model that includes decarbonization targets. This larger improvement, compared to the ESG-enhanced model, likely reflects the aviation industry's heightened exposure to carbon-related risks and investor focus on emissions. Similarly, TUPRS sees a meaningful improvement, with RMSE falling from 2.7023 to 2.5782. Given its likely position in the energy or petrochemical sector, TUPRS is naturally impacted by carbon policies, which can shape both regulatory obligations and investment decisions. In contrast, EREGL and TCELL show only minor improvements, with RMSE reductions of around 0.006 and 0.033, respectively—nearly identical to the gains observed with ESG data alone. This suggests that decarbonization targets do not add much additional predictive value beyond what is already captured by ESG metrics for these stocks. ASELS, however, stands out as an exception. Its RMSE slightly increases from 1.7859 to 1.8377 after adding decarbonization data, implying a misalignment between these variables and the drivers of its stock performance. This may be due to ASELS's industry—possibly defense or electronics—where carbon-related issues are less central, making such data less relevant and potentially introducing noise into the model.

Table 8. Error Metrics - Third Case: Price + Decarbonization

Stock	MAE	MSE	RMSE
ASELS	1.2823	3.3772	1.8377
EREGL	0.3706	0.2617	0.51157
TCELL	1.5402	4.1908	2.0472
THYAO	4.229	30.469	5.5199
TUPRS	2.0673	6.647	2.5782

Overall, companies operating in sectors with high emissions exposure—THYAO and TUPRS—showed the strongest improvements in prediction accuracy when these targets were added. For example, THYAO’s RMSE dropped significantly, suggesting that investors actively respond to decarbonization plans in high-impact industries. In aviation, where emissions reduction is difficult and regulation is tightening (e.g., EU ETS, CORSIA), carbon targets may be a proxy for operational viability, investment risk, or access to green capital. Likewise, TUPRS, operating in oil refining—a fossil-fuel-intensive industry—benefited significantly from decarbonization data. The LSTM model’s improved distributional fit in this case suggests it could better approximate price behavior by integrating transition-relevant features like emission reduction timelines, capital expenditures on cleaner tech, and strategic alignment with low-carbon pathways. By contrast, ASELS exhibited a slight decline in performance when decarbonization targets were added. This likely stems from the limited role that carbon emissions play in the defense industry’s valuation or regulatory risk profile. Including such features in the model may have added noise without improving explanatory power. TCELL and EREGL both showed similar, marginal gains with decarbonization data as they did with ESG scores. This indicates that while transition data may not drastically shift their price behavior, it still holds some predictive value, likely reflecting broader institutional investor sentiment.

The empirical results of this study align in part with the broader academic literature on the relationship between ESG factors and stock performance, though they also raise important differences. A substantial body of research, including studies by Yoon et al. (2018), Deng and Cheng (2019), and Berg et al. (2022), has demonstrated a positive association between strong ESG performance and improved stock valuation or returns, particularly in environmentally or socially sensitive sectors. This aligns with the modest yet consistent improvements observed in the results when ESG and decarbonization data were integrated into predictive models. Stocks such as TUPRS and THYAO, which showed noticeable declines in RMSE with the inclusion of these factors, may reflect the dynamics identified in prior studies, where firms exposed to environmental risks respond more significantly to ESG-related inputs. In addition, these results reflect the conclusions of Lapinskienė et al. (2023) and Gül and Altuntaş (2024), who emphasize the importance of environmental metrics and their heightened effects in emerging markets. The companies in this study operate in an emerging country, further supporting this interpretation.

However, the improvements in forecasting accuracy are generally small, and in some cases such as EREGL almost negligible. This brings into question the overall relevance of ESG information across all sectors and companies. Similar concerns are raised in studies by Halbritter and Dorfleitner (2015), La Torre et al. (2020), and Luo (2022), who argue that ESG factors may not always affect financial performance or that their influence depends on the specific context, such as industry type, geographic location, or investor preferences. The findings of this study point to the same idea: while ESG and decarbonization data can improve model accuracy in certain cases, their overall impact is limited and not consistent across all firms. This suggests a need for more detailed analyses that consider how relevant ESG factors are for different sectors or companies. It also points to the importance of improving methods used to capture the complex relationship between sustainability data and financial outcomes. Additionally, the inconsistency may also stem from discrepancies among ESG scores from different providers (e.g., MSCI, LSEG, Sustainalytics). As Dorfleitner et al. (2015) note, these scores often conflict and may not accurately reflect a company’s true sustainability practices, increasing the risk of

misinterpretation. Overall, the study shows that ESG data can be useful in stock prediction, but its value is uneven and should be used carefully in financial modeling.

5. Conclusion

This study explored the effectiveness of an LSTM-based model in predicting stock prices using a combination of historical financial data and sustainability metrics, specifically ESG scores and corporate decarbonization targets. Using data from five BIST 100 companies between 1 January 2020 and 19 March 2025, the study examined how the inclusion of these non-financial variables affected predictive performance across different sectors.

The results show that the integration of sustainability data produced mixed outcomes. In high-emission sectors such as aviation (THYAO), oil refining (TUPRS), and steel production (EREGL), the inclusion of ESG and decarbonization data led to improvements in model accuracy, as measured by MAE, MSE, and RMSE. THYAO exhibited the most significant gains, particularly with decarbonization targets—likely due to the strong regulatory and investor focus on climate performance in the airline industry. TUPRS also saw notable improvements, aligning with the oil sector’s exposure to energy transition risks. Interestingly, the results for EREGL were more modest than expected. Given the steel industry’s substantial carbon footprint and increasing regulatory and market pressure to adopt low-emission practices, a higher sensitivity to sustainability metrics was anticipated. In contrast, companies in sectors less directly impacted by environmental pressures responded differently. TCELL, representing the telecom industry, showed moderate improvements, particularly with ESG inputs, but limited sensitivity to decarbonization data. For ASELS, a defense and aerospace firm, ESG scores offered only marginal predictive value, and decarbonization inputs slightly degraded model performance—reflecting the sector’s misalignment with conventional sustainability frameworks.

Overall, while the improvements are not dramatic, the findings suggest that sustainability metrics can enhance LSTM model performance when they are materially relevant to a company’s core operations. However, their predictive value is not universal. The study highlights the importance of aligning input features with sector-specific realities. While LSTM proved effective at modeling complex, time-dependent relationships, the results underline that thoughtful feature selection—based on contextual relevance—is key to achieving meaningful gains in predictive accuracy.

The present study’s findings are shaped by the specific ESG measurement framework used; as different providers often produce conflicting ratings, results may vary by data source. To improve external validity, future work should incorporate multiple ESG providers to address issues of measurement error and timing. Additionally, future studies should consider including a larger and more diverse set of companies, both in terms of geography and industry, to make the findings more broadly applicable. Exploring other deep learning models, such as GRUs or Transformers, could also help identify which approaches work best for stock prediction. Finally, combining ESG data with macroeconomic indicators or market sentiment could provide a fuller picture of investor behavior and improve the practical value of sustainability-focused forecasting. Furthermore, policymakers should encourage companies to share more detailed ESG and decarbonization information, as this can help investors and analysts make better predictions and

decisions. Standardizing ESG data across industries would make it easier to compare companies and assess their long-term value.

In addition, future research should investigate the temporal dynamics of ESG and decarbonization data, examining how their predictive value evolves alongside regulatory changes, market shifts, or global events such as the COVID-19 pandemic. Cross-market comparisons between developed and emerging economies could provide deeper insight into how sustainability factors interact with varying institutional environments. Policymakers, meanwhile, should prioritize harmonizing ESG reporting frameworks across jurisdictions to reduce data fragmentation and enable more robust comparative analyses. Encouraging companies to disclose transparent, verifiable, and sector-specific decarbonization strategies would further enhance both academic inquiry and practical forecasting. Finally, integrating explainable AI techniques into sustainability-focused prediction models could improve interpretability, fostering greater trust among investors, regulators, and corporate stakeholders.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement

I am a single author of this paper. My contribution is 100%.

Declaration of Researcher’s Conflict of Interest

There are no potential conflicts of interest in this study.

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EXAMINATION OF FINANCIAL PERFORMANCE OF MANUFACTURING SECTOR COMPANIES IN THE BIST PARTICIPATION SUSTAINABILITY INDEX BY MEREC AND COBRA METHODS

BIST Katılım Sürdürülebilirlik Endeksinde Yer Alan İmalat Sektörü Şirketlerinin Finansal Performansının MEREC ve COBRA Yöntemleriyle İncelenmesi

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Abstract

Measuring corporate financial performance is crucial for maintaining competitive advantage, achieving profitability targets, and ensuring business continuity. The primary aim of this study is to evaluate the financial performance of manufacturing companies listed in the Borsa İstanbul (BIST) Participation Sustainability Index (XSRDK) between 2018 and 2023 by employing the multi-criteria decision-making (MCDM) methods MEREC and COBRA. The dataset consists of 13 manufacturing firms included in the index and eight financial ratios used as evaluation criteria. In the analysis, the MEREC method was applied to determine the weights of the criteria, while the COBRA method was used to rank the firms. A sensitivity analysis was conducted to assess the robustness of the results. Comparisons with alternative MCDM methods and weighting approaches revealed strong correlations across the yearly rankings, supporting the consistency and reliability of the proposed MEREC-COBRA approach in financial performance evaluation.

Keywords:

Participation
Sustainability Index,
Financial Performance,
Manufacturing Sector,
MEREC,
COBRA,
Multi-Criteria
Decision Making

JEL Codes:

G10, G30, Q56

Öz

Şirketlerin finansal performanslarının ölçülmesi, rekabette üstünlüğün sağlanması, karlılık hedeflerine ulaşılması ve faaliyetlerin sürekliliği açısından önemlidir. Bu çalışmanın temel amacı, Borsa İstanbul (BIST) Katılım Sürdürülebilirlik Endeksi'nde (XSRDK) yer alan imalat sektörü şirketlerinin 2018-2023 yılları arasındaki finansal performanslarının çok kriterli karar verme yöntemlerinden MEREC ve COBRA yöntemleri ile incelenmesidir. Çalışmanın veri seti, BIST Katılım Sürdürülebilirlik Endeksi'nde yer alan ve imalat sektöründe faaliyet gösteren 13 şirket ile çalışmada kriter olarak kullanılan sekiz (8) adet finansal orandan oluşmaktadır. Analizlerde MEREC yöntemi ile kriterlerin önem ağırlıkları tespit edilirken, COBRA yöntemi ile firmalar arasındaki performans sıralaması belirlenmiştir. Analiz sonuçlarının güvenilirliğini test etmek amacıyla duyarlılık analizi gerçekleştirilmiştir. Farklı çok kriterli karar verme (ÇKKV) yöntemleri ve kriter ağırlıklandırma yaklaşımlarıyla yapılan karşılaştırmalar, yıllar itibarıyla elde edilen sıralamaların birbirleriyle güçlü bir korelasyona sahip olduğunu göstermiştir. Bu bulgu, çalışmada önerilen MEREC-COBRA yaklaşımının diğer yöntemlerle tutarlı ve güvenilir sonuçlar verdiğini desteklemektedir.

Anahtar Kelimeler:

Katılım
Sürdürülebilirlik
Endeksi,
Finansal Performans,
İmalat Sektörü,
MEREC,
COBRA,
Çok Kriterli Karar
Verme

JEL Kodları:

G10, G30, Q56

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1. Introduction

Sustainability is defined as a method of managing financial risks, environmental risks, and social risks, duties, and opportunities of companies (Brescia et al., 2021: 45). In other words, sustainability can be defined as economic development based on the use of renewable or replaceable resources, taking into account the environmental consequences of the activities related to the economy (Gedik, 2020: 205). The concept of sustainability can be considered one of the priority business areas that takes into account the work of companies in economic, social, and environmental dimensions. Today, investment forms known as socially responsible investments or morally responsible investments, which correspond to investments in financial instruments that attach importance to a sustainable environment, are called green investments or ethical investments (Ghoul and Karam, 2007: 96). The concepts altruism and social justice are interrelated with green investments that aim to contribute to the proper use of natural resources and environmental sustainability. Similarly, Islamic rules such as the prohibition of interest and waste and issues such as charity and zakat based on Islam can also be evaluated in terms of ethical values, social justice, and environmental sustainability (Güçlü, 2019: 248). Islamic stock indices, which are part of Islamic finance, are known as participation indices in our country. According to this index, firms are evaluated in terms of rules based on Islam, and firms that meet the relevant conditions are included in the index (Göktaş and Güçlü, 2023: 226). In this context, it can be said that green investments, known as morally responsible investments, and participation indices created within the framework of Islamic finance rules are related to each other in terms of giving importance to concepts such as social justice, altruism, ethical values, and a sustainable environment.

The BIST Participation Sustainability Index, which was first published by Borsa Istanbul (BIST) in 2021, includes companies that meet both the BIST Sustainability and BIST Participation index conditions (BIST, 2024). The BIST Participation Sustainability Index is a service offered within the framework of Islamic finance for investors who want to invest in shares that overlap with sustainability principles, and at the same time, are related to participation principles (Kılıçarslan, 2022: 1). The BIST Participation Sustainability Index is an indicator of the existence of a relationship between sustainability and Islamic finance. Therefore, the stocks of the companies included in the relevant index are considered to be a suitable option, especially for investors who aim to invest within the framework of social responsibility or Islamic rules. However, considering the development of the index and the criteria for inclusion, it should not be overlooked that it is not exclusively an investment instrument for investors with Islamic sensitivity. Strong financial performance is one of the factors affecting rational investment decisions. Financial performance is an indicator that provides information to investors about the future performance of enterprises. At the same time, it enables to determination of how effectively the existing resources of the enterprises and the assets obtained from them are used (Arman et al., 2022: 803). Financial performance is the competitiveness and risk-taking ability of an enterprise for investment and profitability targets (Karatepe, 2008: 89). Financial performance evaluation is a measurement that plays an important role in the development and change of enterprises in different sectors.

The aim of this study is to measure the financial performance of the manufacturing sector companies registered in the BIST Participation Sustainability Index between 2018 and 2023 with integrated MCDM approaches. The place of the manufacturing sector in a country's economy is the most fundamental indicator of that country's development process (Polat, 2011: 25). If

developing countries have a sufficiently strong manufacturing industry, they grow faster than other countries and increase their welfare level rapidly. In addition, technological advances in the manufacturing sector spread to other sectors over time and increase the productivity of these sectors (Strategy and Budget Presidency, 2018). In the study, MEREC (Method Based on the Removal Effects of Criteria), one of the objective weighting methods, and COBRA (Comprehensive Distance Based Ranking), a new approach to ranking alternatives, were analyzed in an integrated manner. In addition, the validity and robustness of the model used in the study were tested by applying sensitivity analysis consisting of two stages.

The most important contribution of this study to the literature is that it employs the integrated model together for the first time in the relevant field. In addition, the study interval of 2018-2023, which covers the pre-pandemic and post-pandemic periods, provides the opportunity to compare the financial performance of companies across these periods, which is one of the study's unique aspects. The manufacturing sector is a sector that includes many interrelated sub-sectors. The impact of the manufacturing sector on others, being a strong building block and crucial for the development of the country's economy, underscores the importance of the study. In addition, the limited number of studies in the literature within the scope of the BIST Participation Sustainability Index and the introduction of new methods to the literature emphasize the importance of the study. The literature section of the study, which consists of six chapters, summarizes the studies on its subject and its methods. In the data set and method section, the data used in the study, the methods applied, and the application steps of these methods are presented in detail. In the findings section, the results obtained from the analyses are presented. In the sensitivity analysis section, the validity and robustness of the proposed model are evaluated by comparing the results obtained from different methods. In the discussion and conclusion section, the results are compared with the results found in similar studies in the literature, and suggestions are made for future studies.

2. Literature Review

Performance measurement in companies enables the assessment of corporate sustainability and success. Financial performance refers to the evaluation of companies achieving economic targets and the profitability and efficiency of company activities (Cebeci and Özbilgin, 2015: 50). It has been observed that multi-criteria decision-making methods are frequently used in studies on financial performance evaluations of manufacturing sector companies. Some of the studies in which MCDM methods are used in the financial performance measurement of companies in manufacturing sectors and sub-sectors traded in BIST are summarized in chronological order. In their study, Aytekin and Sakarya (2013) evaluated the financial performance of 20 food enterprises registered in BIST for the years 2009-2012, using 10 financial ratios with the TOPSIS method. As a result of the analysis, it was concluded that no company consistently performed best over the entire period, due to the 2008 global financial crisis, but there were companies with good performance on a yearly basis. These companies were identified as KRSTL, PNSUT, BANVT, PETUN, and CCOLA. Bakırcı et al. (2014) evaluated the financial performance of 14 companies from the BIST Iron, Steel, Metal Main Industry sector for the period 2009-2011 with DEA Super Efficiency and TOPSIS methods. The Super Efficiency method was used to select the most efficient company among the companies determined as efficient by the DEA method. As a result, EREĞLİ Enterprise was found to be the most efficient company. According to the TOPSIS

method, EREĞLİ company was determined to have the most efficient performance. Akbulut and Rençber (2015) analyzed the financial performance of 32 companies registered in the BIST Manufacturing sector for the years 2010-2012, using the TOPSIS method. In addition to financial performance, the stock market performance of the companies was evaluated in the study. As a result of the analysis, Adana Cement Company was determined as the company with the best financial performance both on a yearly basis and in the overall score. Meydan et al. (2016) used the Grey Relational Analysis (GRA) method in another study on financial performance measurement for BIST Food enterprises. In the study, the financial statement data of 10 companies for the period of 2012 and their financial ratios were analyzed. As a result of the analysis, Ülker Gıda, which exhibited strong performance in terms of profitability ratios, ranked first. Akyüz et al. (2018) evaluated the financial performance of 14 enterprises in the Paper and Paper Products Printing and Publishing sector traded in BIST for the years 2012-2017 by using TOPSIS, PROMETHEE, and COPRAS methods. The analyses showed that similar results were obtained with the TOPSIS and the PROMETHEE methods, while the COPRAS method gave different results in some years compared to the other two methods. It is suggested that this situation is related to the borrowing ratios, which are treated as negative during the application of the COPRAS method, and show excessive deviations in the relevant years. In his study, Işıldak (2018) evaluated the financial performances of 20 enterprises from the BIST Weaving, Clothing, and Leather Enterprises between 2014-2017, utilizing the TOPSIS method using 11 financial ratios. According to the results obtained, DESA company showed the best performance between 2014 and 2016, and BRMEN company showed in 2017. Şahin and Sarı (2019) used Entropy in criteria weighting and TOPSIS and VIKOR methods in ranking alternatives in order to measure the financial performance of 27 manufacturing sector companies registered in BIST for the years 2013-2016 was analyzed. They also investigated the relationship between the financial performance of the companies and their stock market performance. It was emphasized that the use of the Entropy method in criteria weighing and the comparison of financial performance and stock market performance added a unique contribution to the study.

Küçükönder and Şişmanoğlu (2020) analyzed the financial performance of 21 enterprises in the BIST textile and leather sector. Criteria weights were determined by the entropy method, and a hybrid method including the EATWIOS, MAUT, and WASPAS methods was used to evaluate the performance. The study concluded that Entropy-based WASPAS is the most appropriate method for performance analysis and performance ranking of companies in the textile sector. Secondly, the conclusion was that the Entropy-based EATWIOS and the Entropy-based MAUT method gave feasible results. Acar and Sarıyer (2021) analyzed the financial performance of 17 basic metal industry companies registered in BIST by using financial ratios determined for 2017. The AHP method was used for criterion weighting, and the TOPSIS method was used for ranking the companies according to these weights. The companies were ranked and compared according to their closing prices for 2017, and it was observed that both rankings for 15 companies gave similar results. According to the results of this analysis, the conclusion was that it is appropriate to combine AHP and TOPSIS and use them in financial performance evaluation. Yıldırım et al. (2021) analyzed the financial performance of four iron and steel manufacturing companies listed in the BIST Main Metal Index (XMANA) for the 2011–2019 period using the GRA method. Based on seven financial ratios, the company with the highest performance was identified as EREGL in 2011 and 2013, KRDM in 2012, and ISDMR throughout the 2014–2019 period. In his study, Çanakçıoğlu (2022) proposed a new model consisting of MCDM methods

for measuring the financial performance of companies traded in the BIST Textile Index. A model consisting of CRITIC and MAIRCIA methods was proposed based on the criteria set determined in the study. In addition, to ensure the consistency and validity of the model, a comprehensive sensitivity analysis was performed across 99 different scenarios. As a result of the analyses, the suitability of the model was determined. In their study, Kendirli and Yıldırım (2022) evaluated the financial performance of 11 automotive manufacturing companies traded on BIST between 2015 and 2019 using the TOPSIS method. The authors emphasized that the automotive sector is linked to other sectors and acts as a locomotive for the national economy. For this reason, they foresee that financial performance analyses in this sector will contribute to its development and guide the investments to be made. Asker (2022) analyzed the financial performance of 50 manufacturing firms listed on BIST for the 2019–2020 period by applying the CRITIC-based CoCoSo method in the context of the pre-pandemic and pandemic periods of COVID-19. The findings of the study revealed that the food, beverage, and tobacco sector was the most adversely affected by the pandemic, whereas the chemicals, pharmaceuticals, rubber, petroleum, and plastics sector was the least affected. Bardi (2023) examined the financial performance of nine manufacturing sub-sectors operating on BIST for the 2017–2022 period using the GRA method. The study employed 22 financial ratios, and the findings indicated that operating expenses were the most influential factor affecting the financial performance of the sectors. In particular, the reduction of cost of goods sold and financial expenses was found to have a positive impact on performance. Ersoy (2023) analyzed the 2021 financial performance of 39 companies operating in the BIST Chemicals, Petroleum, Rubber, and Plastic Products sector using the SECA method and tested the reliability of the results through sensitivity analysis. In the final ranking obtained via the Copeland method, ANGEN, ALKIM, and ACSEL were identified as the companies with the highest performance. Bozdoğan et al. (2023) examined the financial performance of companies in the cement sector listed on Borsa Istanbul for the 2013–2022 period. In the study, financial ratios frequently cited in the literature were selected as evaluation criteria and weighted using the CRITIC method. For performance measurement, the TOPSIS and ELECTRE methods were applied, whereby companies were both ranked and classified into three performance groups: high, medium, and low. According to the results of the analysis, OYAK, NUHCM, and KONYA were identified as the top-performing companies, while BTCIM was determined to be the company with the lowest performance. Güçlü and Göktaş (2023) evaluated the financial performance of 11 manufacturing sector companies registered in the BIST Participation Sustainability Index for the year 2022, by using Entropy-weighted TOPSIS and PES methods. According to the results of both methods, AKSA was determined as the company with the best performance. With this study, the authors have helped relevant company managers understand their companies' positions among similar companies and develop appropriate policies accordingly. In addition, they have presented a study that can help investors who are considering investing in this sector at the decision-making stage.

Pala et al. (2024) evaluated the financial performance of 16 companies in the BIST Cement Index for the 2020–2022 period using the LODECI and CRADIS methods. The findings revealed the critical importance of return on equity and further demonstrated that companies with low financial performance need to enhance both their return on equity and net profit margins. Arslan (2024) evaluated the financial performance of companies in the textile and apparel sector listed on Borsa Istanbul for the 2020–2022 period using the COPRAS method. According to the analysis, BLCYT was identified as the top-performing firm in 2020 and 2022, while ARSAN was

identified as the top-performing firm in 2021. The lowest-performing companies were KRTEK in 2020, YUNSA in 2021, and ATEKS in 2022. Göktaş (2024), in his two-stage analysis based on the sustainability scores of technology companies in the BIST Participation Sustainability Index, obtained performance scores with the Robust Theoretical Fuzzy Evaluation System (R-FES), one of the fuzzy MCDM approaches, was used made a sustainable portfolio recommendation based on these scores. Ok and Göktaş (2024) also measured the sustainability performance of service sector firms in the BIST Participation Sustainability Index, with R-FES. Özarı and Çanakçıoğlu (2025) analyzed the 2023 financial performance of eight automobile manufacturing firms listed on Borsa İstanbul. The weights of the financial criteria were determined using the CRITIC method, while performance rankings were conducted using the TOPSIS and VIKOR methods. The analysis revealed that the most influential criterion was the ratio of short-term liabilities to total debt. According to the rankings, TTRAK was identified as the top-performing firm under the TOPSIS method, whereas FROTO and TOASA were identified as the top-performing firms under the VIKOR method. Kavas (2025) examined the financial performance of six companies operating in the Basic Metal Industry sector listed on Borsa İstanbul for the 2018–2023 period. The weights of the financial ratios were determined using the ENTROPY method, while performance analyses were conducted using the PROMETHEE II and WASPAS methods. According to the results, Ereğli and İskenderun Demir Çelik were identified as the top-performing firms in the PROMETHEE II rankings, whereas İzmir Demir Çelik, despite demonstrating low performance between 2018 and 2021, rose to higher positions in the last two years. Süzölmüş (2025) analyzed the financial performance of 26 firms operating in the textile, apparel, and leather sectors listed on Borsa İstanbul for the 2020–2023 period. The financial ratios used in the study were weighted using the CRITIC method, while performance rankings were obtained through the COPRAS and MABAC methods. The findings revealed a persistent pattern in performance rankings over the years, with certain companies consistently occupying the top three and bottom three positions.

In recent years, Multi-Criteria Decision-Making (MCDM) methods have been widely employed to evaluate the financial performance of companies listed on Borsa İstanbul. Among these, GRA, TOPSIS, VIKOR, and COPRAS have emerged as commonly applied approaches for analytically assessing corporate financial performance (Yıldırım et al., 2021; Arslan, 2024; Kavas, 2025; Özarı and Çanakçıoğlu, 2025). Although these conventional methods provide valuable insights into financial performance, they exhibit certain limitations in the objective determination of criterion weights and the establishment of reliable performance rankings.

Although the MEREC and COBRA methods are relatively new methods, the number of studies in which they are used in an integrated manner has tended to increase recently. Popović et al. (2022) used MEREC and COBRA methods in the selection process of a strategy for the development of e-commerce, Vatansever (2024) used these methods in proposing an alternative model to university ranking approaches, Oğuz and Satır (2024) used them in measuring the financial performance of BIST retail trade companies, Asker (2024) used them in measuring the financial performance of airline companies, Çıtak and Ünlü (2024) used MEREC and COBRA methods in the performance measurement of banks traded in BIST based on sustainability reports, and Ergün and Bulut (2024) used MEREC and COBRA methods in the measurement of the financial and operating performance of an iron and steel enterprise. In this study, the MEREC and COBRA methods were employed to overcome these limitations and enhance the reliability of the analyses. The MEREC method systematically evaluates the impact of omitting each criterion on

the overall decision, thereby enabling the objective determination of criterion weights and minimizing biases arising from subjective assessments. The COBRA method, on the other hand, provides a compromise ranking mechanism that accounts for both linear and non-linear interactions among criteria, thereby improving the sensitivity and reliability of the performance rankings. The integrated application of the MEREC and COBRA methods not only overcomes the limitations of traditional MCDM approaches but also enhances the analytical rigor of financial performance analyses, providing decision-makers with more reliable, consistent, and meaningful results. The most important contributions of the study to the literature are: there are very few studies about companies within the BIST Participation Sustainability Index; the proposed integrated model is used for the first time in the relevant sector; and the analysis covers the period between 2018-2023, allowing the comparison of the financial performance of the companies in this index before and after the COVID-19 pandemic.

3. Data Set and Methodology

3.1. Data Set

In the study, the financial statement data of the companies registered in the BIST Participation Sustainability Index for the years 2018-2023 were used. Data on companies were obtained from the Borsa Istanbul Public Disclosure Platform (PDP, 2024). As of September 2024, 31 companies were included in the BIST Participation Sustainability Index, of which 13 out of 15 operating in the manufacturing sector were part of the study. QUA Granite Hayal Yapı ve Ürünleri Sanayi Ticaret A.Ş. and SUN Tekstil Sanayi ve Ticaret A.Ş., which are among the manufacturing sector companies, were not included in the study since their financial data for the years 2018-2023 were not available. Table 1 lists the manufacturing sector companies included in the BIST Participation Sustainability Index in alphabetical order.

Table 1. Manufacturing Sector Companies in the BIST Participation Sustainability Index

BIST Code	Company Name
AKCNS	Akçansa Çimento Sanayi ve Ticaret A.Ş.
AKSA	Aksa Akrilik Kimya Sanayii A.Ş.
CCOLA	Coca-Cola İçecek A.Ş.
CIMSA	Çimsa Çimento Sanayi ve Ticaret A.Ş.
EREGL	Ereğli Demir ve Çelik Fabrikaları T.A.Ş.
ISDMR	İskenderun Demir ve Çelik A.Ş.
KRDMD	Kardemir Karabük Demir Çelik Sanayi ve Ticaret A.Ş.
OTKAR	Otokar Otomotiv ve Savunma Sanayi A.Ş.
PETKM	Petkim Petrokimya Holding A.Ş.
SASA	Sasa Polyester Sanayi A.Ş.
TUPRS	Tüpraş-Türkiye Petrol Rafinerileri A.Ş.
VESBE	Vestel Beyaz Eşya Sanayi ve Ticaret A.Ş.
VESTL	Vestel Elektronik Sanayi ve Ticaret A.Ş.

Financial ratios used in financial analyses are the ratios that allow for the examination of a company's balance sheet horizontally and vertically and to establish relationships between items (Sarıkamış, 2007: 44). Within the scope of the study, the financial ratios used in the evaluation of the financial performance of the companies were determined as eight under four main headings. Current ratio and acid test ratio were used to measure liquidity, financial leverage ratio and

financing ratio were used to measure financial structure ratios, asset turnover ratio and inventory turnover ratio were used to measure activity ratios, and net profit margin and return on assets ratio were used to measure profitability. In the selection of the financial ratios in the study, those frequently used in the literature were preferred by examining studies on the manufacturing sector, particularly those evaluating the financial performance of companies registered in BIST. Table 2 shows the financial ratios used in the study.

Table 2. Financial Ratios Used in the Study

Rate Group	Ratio	Direction	Source
Liquidity Ratios	Current Ratio	Benefit	Akbulut and Rençber, 2015; Akyüz and Yeşil, 2017; Arslan, 2024; Çolak, 2023; Aytekin and Sakarya, 2013; Güçlü and Göktaş, 2023; Güleç and Özkan, 2018; Kayalı and Aktaş, 2018; Kılıçarslan, 2022; Meydan et al., 2016; Pala, 2023.
	Acid Test Rate	Benefit	Akbulut and Rençber, 2015; Akyüz and Yeşil, 2017; Arslan, 2024; Güçlü and Göktaş, 2023; Güleç and Özkan, 2018; Kılıçarslan, 2022; Meydan et al., 2016.
Financial Structure Ratios	Financial Leverage Ratio	Cost	Akyüz and Yeşil, 2017; Arslan, 2024; Aytekin and Sakarya, 2013; Güçlü and Göktaş, 2023; Güleç and Özkan, 2018; Kılıçarslan, 2022.
	Financing Rate	Benefit	Akyüz and Yeşil, 2017; Aytekin and Sakarya, 2013; Güleç and Özkan, 2018.
Activity Ratios	Asset Turnover Rate	Benefit	Akbulut and Rençber, 2015; Akyüz and Yeşil, 2017; Güçlü and Göktaş, 2023; Güleç and Özkan, 2018; Kılıçarslan, 2022; Meydan et al., 2016; Pala, 2023.
	Inventory Turnover Rate	Benefit	Akbulut and Rençber, 2015; Akyüz and Yeşil, 2017; Arslan, 2024; Güçlü and Göktaş, 2023; Kayalı and Aktaş, 2018; Kılıçarslan, 2022; Meydan et al., 2016.
Profitability Ratios	Return on Assets Ratio	Benefit	Akbulut and Rençber, 2015; Akyüz and Yeşil, 2017; Arslan, 2024; Çolak, 2023; Güçlü and Göktaş, 2023; Kılıçarslan, 2022; Meydan et al., 2016; Pala, 2023.
	Net Profit Margin	Benefit	Akbulut and Rençber, 2015; Güçlü and Göktaş, 2023; Kılıçarslan, 2022; Meydan et al., 2016; Pala, 2023.

In the data set of the study, 13 manufacturing companies were used as alternatives, and 8 financial ratios as criteria. Table 3 lists the alternatives and criteria sets used in this study.

Table 3. Alternatives and Criteria Used in the Study

Code	Alternatives	Code	Criteria
A1	AKCNS	C1	Current Ratio
A2	AKSA	C2	Acid Test Rate
A3	CCOLA	C3	Financial Leverage Ratio
A4	CIMSA	C4	Financing Rate
A5	EREGL	C5	Asset Turnover Rate
A6	ISDMR	C6	Inventory Turnover Rate
A7	KRDMD	C7	Return on Assets Ratio
A8	OTKAR	C8	Net Profit Margin
A9	PETKM		
A10	SASA		
A11	TUPRS		
A12	VESBE		
A13	VESTL		

3.2. Methodology

In this study, while the importance weights of the criteria were determined by the MEREC method, the performance ranking of the firms was determined by the COBRA method. The process steps related to these methods are given in detail below.

3.2.1. MEREC Method

The MEREC was introduced to the literature by Keshavarz-Ghorabae et al. (2021: 7-9) as one of the MCDM methods. With this method, the impact of removing each criterion on the performance of the alternatives is used to determine the criteria weights. Criteria with a greater impact on performance are given higher weights. The following steps are used when calculating objective weights according to the MEREC method (Keshavarz-Ghorabae et al., 2021: 7-9):

Step 1. Creating the Decision Matrix:

A decision matrix showing the rating of each alternative is created where n represents alternatives and m represents criteria. This matrix consists of x_{ij} elements greater than zero. Here are $\forall i = 1, \dots, n$ and $\forall j = 1, \dots, m$. If there are elements with negative values in the decision matrix, they should be converted to positive values by appropriate operations. The form of the decision matrix is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

Step 2. Determination of the Normalized Decision Matrix:

In this step, the decision matrix is normalized using Equation (2) below. The elements of the normalized matrix are denoted by n_{ij}^x . B where C is the set of benefit criteria and is the set of cost criteria;

$$n_{ij}^x = \begin{cases} \frac{\min x_{kj}}{x_{ij}} & \text{if } j \in B \\ \frac{x_{ij}}{\max x_{kj}} & \text{if } j \in C \end{cases} \quad (2)$$

Step 3. Finding the Total Performance Value (S_i):

The total performance value of the alternatives (S_i) is calculated with the help of Equation (3) below.

$$S_i = \ln \left(1 + \left(\frac{1}{m} \sum_j | \ln(n_{ij}^x) | \right) \right) \quad (3)$$

Step 4. Finding the Performance of Alternatives (S'_{ij}):

Each criterion is extracted separately, and the performance of the alternatives is determined using Equation (4). S'_{ij} represents the overall performance of the alternative i excluding the criterion j .

$$S'_{ij} = \ln \left(1 + \left(\frac{1}{m} \sum_{k, k \neq j} |\ln(n_{ik}^x)| \right) \right) \quad (4)$$

Step 5. Calculation of the Sum of Absolute Deviations (E_j):

In this step, the lifting effect (E_j) of criterion j is calculated by substituting the values calculated using Equations (3) and (4) in Equation (5).

$$E_j = \sum_i |S'_{ij} - S_i| \quad (5)$$

Step 6. Calculation of Importance Weights of Criteria (w_j):

In this last step, the objective weight of each criterion is calculated with the help of the lifting effects (E_j) obtained in Equation (5). Here, w_j , denotes the weight of the j . criterion.

$$w_j = \frac{E_j}{\sum_k E_k} \quad (6)$$

3.2.2. COBRA Method

The COBRA method is a new method introduced to the literature by Krstić et al. (2022). It is a distance-based MCDM method that differs from other distance-based methods by offering positive and negative ideal solution points derived from averages, and by using both Euclidean and taxicab distance measurement methods together. This method is used in the evaluation and ranking of alternatives. The steps of the method are listed as follows:

Step 1. Creating the Decision Matrix:

As explained in the MEREC method section, $i = (1, 2, \dots)$ alternatives, $j = (1, 2, \dots, m)$ criteria, A decision matrix is created.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix}$$

Step 2. Creating the Normalized Decision Matrix:

The normalized decision matrix Δ in Equation (7) is constructed.

$$\Delta = [\alpha_{ij}]_{n \times m} \quad (7)$$

$$\alpha_{ij} = \frac{a_{ij}}{\max_i a_{ij}} \quad (8)$$

Step 3. Constructing the Weighted Normalized Decision Matrix:

Equation (9) is used to create a normalized decision matrix weighted by Δ_w . Here, w_j, j is the relative weight of the criterion.

$$\Delta_w = [w_j \times \alpha_{ij}]_{n \times m} \quad (9)$$

Step 4. Determination of Positive Ideal, Negative Ideal and Average Solution for the Criteria:

For each criterion, the positive ideal (PIS_j), negative ideal (NIS_j), and average solution (AS_j), are determined as in Equations (10), (11) and (12) respectively. Here, J^B is the set of benefit criteria and J^C is the set of cost criteria.

$$\begin{aligned} PIS_j &= \max_i (w_j \times \alpha_{ij}), \quad \forall j = 1, \dots, m. \quad j \in J^B \\ PIS_j &= \min_i (w_j \times \alpha_{ij}), \quad \forall j = 1, \dots, m. \quad j \in J^C \end{aligned} \quad (10)$$

$$\begin{aligned} NIS_j &= \min_i (w_j \times \alpha_{ij}), \quad \forall j = 1, \dots, m. \quad j \in J^B \\ NIS_j &= \max_i (w_j \times \alpha_{ij}), \quad \forall j = 1, \dots, m. \quad j \in J^C \end{aligned} \quad (11)$$

$$AS_j = \frac{\sum_{i=1}^n (w_j \times \alpha_{ij})}{n}, \quad \forall j = 1, \dots, m. \quad j \in J^B, J^C \quad (12)$$

Step 5. In this step, the distances from the positive ideal ($d(PIS_j)$) and negative ideal ($d(NIS_j)$) solutions are found for each alternative. In addition, the positive ($d(AS_j^+)$) and negative ($d(AS_j^-)$) distances from the average solution are determined as follows.

$$d(S_j) = dE(S_j) + \sigma \times dE(S_j) \times dT(S_j), \quad \forall j = 1, \dots, m \quad (13)$$

where σ is the correction coefficient in Equation (14) for any S_j solution (PIS_j, NIS_j, AS_j).

$$\sigma = \max_i dE(S_j)_i - \min_i dE(S_j)_i \quad (14)$$

$dE(S_j)_i$ and $dT(S_j)_i$ to denote Euclidean and Taxicab distances respectively;

The calculated positive ideal solution is as in Equations (15) and (16). Here is $\forall i = 1, \dots, n$ and $\forall j = 1, \dots, m$.

$$dE(PIS_j)_i = \sqrt{\sum_{j=1}^m (PIS_j - w_j \times \alpha_{ij})^2} \quad (15)$$

$$dT(PIS_j)_i = \sum_{j=1}^m |PIS_j - w_j \times \alpha_{ij}| \quad (16)$$

The negative ideal solution obtained is as in Equation (17) and Equation (18). Here is $\forall i = 1, \dots, n$ and $\forall j = 1, \dots, m$.

$$dE(NIS_j)_i = \sqrt{\sum_{j=1}^m (NIS_j - w_j \times \alpha_{ij})^2} \quad (17)$$

$$dT(NIS_j)_i = \sum_{j=1}^m |NIS_j - w_j \times \alpha_{ij}| \quad (18)$$

Equations obtained for positive distance from the average solution are as follows. Here is $\forall i = 1, \dots, n$ and $\forall j = 1, \dots, m$.

$$dE(AS_j)_i^+ = \sqrt{\sum_{j=1}^m \tau^+ (AS_j - w_j \times \alpha_{ij})^2} \quad (19)$$

$$dT(AS_j)_i^+ = \sum_{j=1}^m \tau^+ |AS_j - w_j \times \alpha_{ij}| \quad (20)$$

$$\tau^+ = \begin{cases} 1, & AS_j < w_j \times \alpha_{ij} \\ 0, & AS_j > w_j \times \alpha_{ij} \end{cases} \quad (21)$$

The Equations determined for the negative distance from the mean solution are as follows. Here is $\forall i = 1, \dots, n$ and $\forall j = 1, \dots, m$.

$$dE(AS_j)_i^- = \sqrt{\sum_{j=1}^m \tau^- (AS_j - w_j \times \alpha_{ij})^2} \quad (22)$$

$$dT(AS_j)_i^- = \sum_{j=1}^m \tau^- |AS_j - w_j \times \alpha_{ij}| \quad (23)$$

$$\tau^- = \begin{cases} 1, & AS_j > w_j \times \alpha_{ij} \\ 0, & AS_j < w_j \times \alpha_{ij} \end{cases} \quad (24)$$

Step 6. Finally, in this step, Equation (25) is used to rank the alternatives according to the comprehensive distances. Here it is $\forall i = 1, \dots, n$.

$$dC_i = \frac{d(PIS_j)_i - d(NIS_j)_i - d(AS_j)_i^+ + d(AS_j)_i^-}{4} \quad (25)$$

4. Findings

In the study, the financial performances from 2018 to 2023 of 13 manufacturing sector companies, traded in the BIST Participation Sustainability Index as of September 2024, were analyzed by MEREC and COBRA methods. Before the analysis phase, a decision matrix containing the data and alternatives related to the financial ratios used to evaluate the companies was created. The decision matrix obtained with the financial statement data of the companies for

the years 2018-2023 is shown in Table 4. For the integrity of the study, only the analyses for 2023 are included, and the results for other years are presented in the last part of the study.

Table 4. Decision Matrix for 2018-2023

2018								
Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.152	0.868	48.736	1.052	0.842	6.820	0.088	10.478
A2	1.190	0.954	65.443	0.528	0.938	6.450	0.059	6.340
A3	1.700	1.399	53.990	0.852	0.775	10.377	0.026	3.390
A4	0.654	0.522	58.339	0.714	0.505	7.679	0.046	9.051
A5	2.854	1.727	29.983	2.335	0.770	2.675	0.167	21.635
A6	3.363	2.062	25.040	2.994	0.912	3.457	0.236	25.871
A7	1.384	0.603	50.356	0.986	0.736	3.227	0.107	14.585
A8	2.076	1.281	83.082	0.204	0.779	1.969	0.076	9.790
A9	2.070	1.778	67.151	0.489	0.914	7.647	0.082	8.978
A10	1.248	0.777	58.199	0.718	0.667	4.122	0.183	27.417
A11	1.314	0.890	75.158	0.331	2.265	13.160	0.096	4.248
A12	1.115	0.904	61.333	0.630	1.476	8.861	0.161	10.934
A13	0.740	0.529	81.525	0.227	0.997	3.986	0.025	2.529
2019								
Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.175	0.896	48.199	1.075	0.876	7.383	0.036	4.105
A2	1.052	0.728	63.342	0.579	0.871	5.228	0.066	7.616
A3	1.545	1.299	53.825	0.858	0.817	9.595	0.063	7.695
A4	0.783	0.646	60.639	0.649	0.476	7.584	0.004	0.880
A5	2.554	1.567	33.050	2.026	0.621	2.465	0.079	12.722
A6	3.323	1.956	25.115	2.982	0.772	3.354	0.101	13.100
A7	1.057	0.503	57.004	0.754	0.704	3.261	0.009	1.327
A8	1.872	1.132	76.187	0.313	0.976	2.073	0.141	14.465
A9	1.861	1.680	67.240	0.487	0.852	9.784	0.056	6.547
A10	0.477	0.254	66.662	0.500	0.464	3.732	0.179	38.505
A11	0.993	0.656	76.335	0.310	1.876	10.437	0.012	0.653
A12	1.059	0.843	63.758	0.568	1.441	9.930	0.118	8.153
A13	0.656	0.462	80.568	0.241	0.918	4.529	0.019	2.049
2020								
Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.238	1.023	50.365	0.986	0.886	9.051	0.052	5.838
A2	1.460	1.113	62.116	0.610	0.902	4.821	0.097	10.705
A3	1.773	1.532	54.371	0.839	0.820	9.745	0.075	9.132
A4	0.870	0.792	64.149	0.559	0.466	7.782	0.041	8.883
A5	3.022	1.950	29.093	2.437	0.612	2.688	0.067	10.952
A6	4.601	2.970	22.448	3.455	0.677	3.185	0.097	14.319
A7	1.024	0.646	63.925	0.564	0.758	3.576	0.006	0.807
A8	1.495	0.867	76.758	0.303	0.830	1.630	0.176	21.256
A9	1.999	1.837	62.176	0.608	0.698	10.862	0.062	8.828
A10	0.626	0.325	73.250	0.365	0.544	3.783	0.034	6.193
A11	1.082	0.810	80.917	0.236	1.084	7.162	0.042	3.831
A12	1.260	1.046	59.152	0.691	1.424	9.511	0.202	14.149
A13	0.805	0.567	72.578	0.378	0.926	4.504	0.082	8.852

Table 4. Continued

2021								
Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.999	0.569	55.966	0.787	0.968	5.144	0.102	10.574
A2	1.020	0.756	69.986	0.429	1.162	5.940	0.162	13.982
A3	1.432	1.098	54.341	0.840	0.845	8.026	0.093	11.039
A4	1.157	0.797	47.171	1.120	0.722	6.548	0.202	28.045
A5	2.798	1.565	33.133	2.018	0.740	2.187	0.174	23.566
A6	3.026	1.406	29.770	2.359	0.868	2.461	0.154	17.722
A7	1.286	0.953	54.336	0.840	0.905	3.980	0.236	26.094
A8	1.388	0.888	75.014	0.333	0.873	2.022	0.202	23.099
A9	2.563	2.101	58.200	0.718	1.139	9.914	0.219	19.211
A10	0.982	0.555	81.244	0.231	0.888	4.175	0.00004	0.005
A11	1.022	0.651	82.613	0.210	1.844	8.616	0.042	2.276
A12	1.182	0.873	65.519	0.526	1.443	7.559	0.135	9.387
A13	0.682	0.371	76.071	0.315	0.926	3.456	0.061	6.626
2022								
Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.105	0.862	54.511	0.834	1.539	8.539	0.263	17.088
A2	1.420	0.913	49.722	1.011	1.673	6.998	0.328	19.606
A3	1.631	1.243	61.176	0.635	1.170	7.879	0.101	8.670
A4	1.190	0.964	47.334	1.113	1.019	7.788	0.423	41.507
A5	2.246	1.017	32.152	2.110	0.848	2.797	0.124	14.597
A6	2.322	0.880	30.646	2.263	0.951	3.156	0.103	10.847
A7	1.300	0.671	56.977	0.755	1.131	4.152	0.090	7.936
A8	1.061	0.674	85.140	0.175	0.954	2.477	0.123	12.902
A9	1.103	0.962	65.133	0.535	1.149	11.304	0.154	13.385
A10	0.545	0.212	68.699	0.456	0.832	3.822	0.284	34.094
A11	1.517	1.060	60.220	0.661	3.550	14.013	0.304	8.564
A12	0.923	0.683	75.247	0.329	1.580	7.490	0.072	4.538
A13	0.616	0.344	79.015	0.266	1.102	4.012	0.021	1.898
2023								
Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.449	1.159	29.645	2.373	1.353	11.691	0.171	12.664
A2	1.418	0.918	33.066	2.024	1.314	7.071	0.091	6.903
A3	1.163	0.850	59.191	0.689	1.197	6.918	0.251	20.942
A4	1.362	1.039	38.951	1.567	0.820	8.263	0.123	15.014
A5	1.507	0.753	38.223	1.616	0.610	2.399	0.018	2.927
A6	1.525	0.685	36.563	1.735	0.843	3.224	0.044	5.193
A7	1.311	0.673	38.558	1.594	1.192	4.888	0.037	3.076
A8	1.152	0.797	74.440	0.343	1.168	3.705	0.084	7.225
A9	0.760	0.531	46.354	1.157	0.803	11.929	0.099	12.266
A10	0.817	0.494	56.623	0.766	0.454	3.735	0.178	39.278
A11	1.295	1.009	44.672	1.239	2.563	14.329	0.201	7.847
A12	1.051	0.764	57.596	0.736	1.598	8.767	0.124	7.736
A13	0.616	0.315	67.359	0.485	1.193	4.812	0.025	2.077

The criteria values in the decision matrix are calculated according to the financial ratios listed in Table 2. The data used for financial ratios were obtained from the Public Disclosure Platform (PDP, 2024). In the study, first, the weights of the criteria were determined using the MEREC Method, and then the alternative rankings were calculated via the COBRA Approach.

4.1. Calculation of Criteria Weights with MEREC Method

In this part of the study, criterion weights were determined by the MEREC method. In order to prevent table density and potential confusion, detailed results are presented only for 2023, while the same analytical procedures have been consistently applied to the other years. Table 5 presents the decision matrix for the year 2023.

Table 5. Decision Matrix for 2023

	C1	C2	C3	C4	C5	C6	C7	C8
A1	1.449	1.159	29.645	2.373	1.353	11.691	0.171	12.664
A2	1.418	0.918	33.066	2.024	1.314	7.071	0.091	6.903
A3	1.163	0.850	59.191	0.689	1.197	6.918	0.251	20.942
A4	1.362	1.039	38.951	1.567	0.820	8.263	0.123	15.014
A5	1.507	0.753	38.223	1.616	0.610	2.399	0.018	2.927
A6	1.525	0.685	36.563	1.735	0.843	3.224	0.044	5.193
A7	1.311	0.673	38.558	1.594	1.192	4.888	0.037	3.076
A8	1.152	0.797	74.440	0.343	1.168	3.705	0.084	7.225
A9	0.760	0.531	46.354	1.157	0.803	11.929	0.099	12.266
A10	0.817	0.494	56.623	0.766	0.454	3.735	0.178	39.278
A11	1.295	1.009	44.672	1.239	2.563	14.329	0.201	7.847
A12	1.051	0.764	57.596	0.736	1.598	8.767	0.124	7.736
A13	0.616	0.315	67.359	0.485	1.193	4.812	0.025	2.077

Equation (2) was used to normalise the decision matrix given in Table 5, resulting in the formation of the normalised decision matrix presented in Table 6.

Table 6. Normalised Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.425	0.272	0.398	0.145	0.335	0.205	0.104	0.164
A2	0.434	0.343	0.444	0.170	0.345	0.339	0.197	0.301
A3	0.530	0.370	0.795	0.498	0.379	0.347	0.071	0.099
A4	0.452	0.303	0.523	0.219	0.553	0.290	0.145	0.138
A5	0.409	0.418	0.513	0.212	0.743	1.000	1.000	0.710
A6	0.404	0.460	0.491	0.198	0.538	0.744	0.408	0.400
A7	0.469	0.468	0.518	0.215	0.380	0.491	0.487	0.675
A8	0.534	0.395	1.000	1.000	0.388	0.648	0.212	0.288
A9	0.810	0.593	0.623	0.297	0.564	0.201	0.181	0.169
A10	0.753	0.637	0.761	0.448	1.000	0.642	0.100	0.053
A11	0.475	0.312	0.600	0.277	0.177	0.167	0.089	0.265
A12	0.586	0.412	0.774	0.466	0.284	0.274	0.144	0.269
A13	1.000	1.000	0.905	0.709	0.380	0.499	0.720	1.000

With the help of the values in Table 6 and Equation (3), the total performance values (S_i) of the alternatives were found. In the next step, alternative performances (S'_{ij}) were calculated using Equation (4). Table 7 presents the total performance values of the alternatives (S_i) and the specific performance values of a different metric or criterion (S'_{ij}).

Table 7. S_i and S'_{ij} Performance Values

	S_i	S'_{ij}							
		C1	C2	C3	C4	C5	C6	C7	C8
A1	1.371	1.315	1.285	1.311	1.240	1.299	1.265	1.216	1.249
A2	1.214	1.150	1.131	1.151	1.072	1.131	1.130	1.085	1.120
A3	1.219	1.171	1.143	1.202	1.166	1.145	1.138	1.002	1.032
A4	1.245	1.186	1.155	1.197	1.129	1.201	1.152	1.095	1.092
A5	0.768	0.658	0.661	0.688	0.570	0.733	0.768	0.768	0.727
A6	0.988	0.900	0.913	0.920	0.825	0.929	0.960	0.901	0.899
A7	0.965	0.890	0.890	0.900	0.807	0.868	0.895	0.894	0.927
A8	0.890	0.823	0.789	0.890	0.890	0.787	0.844	0.716	0.753
A9	1.105	1.088	1.061	1.065	0.999	1.057	0.963	0.953	0.946
A10	1.055	1.030	1.015	1.031	0.983	1.055	1.016	0.832	0.760
A11	1.320	1.269	1.239	1.285	1.230	1.197	1.193	1.143	1.227
A12	1.119	1.074	1.044	1.098	1.055	1.010	1.007	0.947	1.005
A13	0.476	0.476	0.476	0.460	0.421	0.313	0.361	0.423	0.476

Then, the sum of the absolute deviations (E_j) was calculated using Equation (5). In the last step, the importance weights (w_j) of the criteria were determined by using Equation (6). These values are presented in Table 8.

Table 8. E_j and w_j Values

	C1	C2	C3	C4	C5	C6	C7	C8
E_j	0.704	0.933	0.536	1.348	1.008	1.043	1.759	1.522
w_j	0.080	0.105	0.061	0.152	0.114	0.118	0.199	0.172

When the results obtained from Table 8 are analyzed, it is seen that the first three criteria with the highest weights are Return on Assets Ratio, Net Profit Margin, and Financing Ratio, respectively. The criteria with relatively low importance weights are the Financial Leverage Ratio and the Current Ratio.

4.2. Ranking Alternatives with the COBRA Method

When the steps of the COBRA Method are analyzed, the first step is the creation of the decision matrix, as in the other MCDM methods. The decision matrix data used in the first stage of the MEREC Method and shown in Table 5 are also valid for the COBRA Method. Since the two methods differ in the data normalization stage, the analysis started with the normalized decision matrix created using Equation (8) and presented in Table 9.

Table 9. Normalized Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.950	1.000	0.398	1.000	0.528	0.816	0.684	0.322
A2	0.930	0.792	0.444	0.853	0.513	0.493	0.362	0.176
A3	0.762	0.733	0.795	0.291	0.467	0.483	1.000	0.533
A4	0.893	0.897	0.523	0.660	0.320	0.577	0.492	0.382
A5	0.988	0.650	0.513	0.681	0.238	0.167	0.071	0.075
A6	1.000	0.591	0.491	0.731	0.329	0.225	0.175	0.132
A7	0.860	0.580	0.518	0.671	0.465	0.341	0.146	0.078
A8	0.756	0.688	1.000	0.145	0.456	0.259	0.337	0.184
A9	0.498	0.458	0.623	0.488	0.313	0.833	0.393	0.312
A10	0.536	0.426	0.761	0.323	0.177	0.261	0.711	1.000
A11	0.849	0.871	0.600	0.522	1.000	1.000	0.803	0.200
A12	0.689	0.659	0.774	0.310	0.623	0.612	0.493	0.197
A13	0.404	0.272	0.905	0.204	0.466	0.336	0.099	0.053

By calculating the values in the normalized decision matrix with the criterion weights obtained in the MEREC method, with the help of Equation (9), researchers obtained the weighted normalized decision matrix presented in Table 10.

Table 10. Weighted Normalized Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8
A1	0.076	0.105	0.024	0.152	0.060	0.096	0.136	0.055
A2	0.074	0.083	0.027	0.130	0.058	0.058	0.072	0.030
A3	0.061	0.077	0.048	0.044	0.053	0.057	0.199	0.092
A4	0.071	0.094	0.032	0.101	0.036	0.068	0.098	0.066
A5	0.079	0.068	0.031	0.104	0.027	0.020	0.014	0.013
A6	0.080	0.062	0.030	0.111	0.037	0.027	0.035	0.023
A7	0.068	0.061	0.031	0.102	0.053	0.040	0.029	0.013
A8	0.060	0.072	0.061	0.022	0.052	0.030	0.067	0.032
A9	0.040	0.048	0.038	0.074	0.036	0.098	0.078	0.054
A10	0.043	0.045	0.046	0.049	0.020	0.031	0.141	0.172
A11	0.068	0.092	0.036	0.079	0.114	0.118	0.159	0.034
A12	0.055	0.069	0.047	0.047	0.071	0.072	0.098	0.034
A13	0.032	0.029	0.055	0.031	0.053	0.040	0.020	0.009

Based on Equations (10)-(12), the positive ideal (PIS_j), negative ideal (NIS_j) and average solution (AS_j) for the criteria are determined and shown in Table 11.

Table 11. Positive Ideal, Negative Ideal and Average Solution Values

	C1	C2	C3	C4	C5	C6	C7	C8
PIS_j	0.080	0.105	0.024	0.152	0.114	0.118	0.199	0.172
NIS_j	0.032	0.029	0.061	0.022	0.020	0.020	0.014	0.009
AS_j	0.062	0.070	0.039	0.081	0.052	0.058	0.088	0.048

Euclidean and Taxicab distances from the positive ideal, negative ideal, and mean solution were calculated using Equations (15) to (24). The values obtained are presented in Table 12.

Table 12. Positive Ideal, Negative Ideal, Euclidean and Taxicab Distance Values from Average Solution

	$dE(PIS_j)_i$	$dT(PIS_j)_i$	$dE(NIS_j)_i$	$dT(NIS_j)_i$	$dE(AS_j)_i^+$	$dT(AS_j)_i^+$	$dE(AS_j)_i^-$	$dT(AS_j)_i^-$
A1	0.145	0.259	0.225	0.571	0.102	0.223	0.015	0.015
A2	0.209	0.436	0.156	0.394	0.053	0.082	0.027	0.046
A3	0.165	0.381	0.217	0.449	0.119	0.172	0.036	0.039
A4	0.181	0.413	0.160	0.417	0.040	0.091	0.017	0.022
A5	0.283	0.622	0.107	0.208	0.029	0.040	0.094	0.181
A6	0.259	0.571	0.115	0.259	0.035	0.048	0.070	0.141
A7	0.261	0.579	0.107	0.251	0.023	0.029	0.072	0.128
A8	0.261	0.640	0.084	0.190	0.022	0.025	0.070	0.126
A9	0.215	0.525	0.127	0.305	0.040	0.046	0.037	0.077
A10	0.189	0.461	0.210	0.369	0.135	0.184	0.061	0.134
A11	0.162	0.287	0.222	0.543	0.114	0.221	0.014	0.017
A12	0.216	0.516	0.126	0.314	0.027	0.051	0.037	0.055
A13	0.304	0.757	0.040	0.073	0.016	0.017	0.108	0.246

After this step, using Equation (13) and Equation (14), the positive ideal distance ($d(PIS_j)_i$), negative ideal distance ($d(NIS_j)_i$) and positive ($d(AS_j)_i^+$) and negative distances ($d(AS_j)_i^-$) from the average solution were calculated. The results obtained here were used in Equation (25) to find dC_i values. Table 13 shows the positive ideal distance, negative ideal distance, positive and negative distances from the average solution, and dC_i values.

Table 13. Positive Ideal, Negative Ideal, Distances from Average Solution and dC_i Values

	$d(PIS_j)_i$	$d(NIS_j)_i$	$d(AS_j)_i^+$	$d(AS_j)_i^-$	dC_i
A1	0.150	0.248	0.105	0.015	-0.047
A2	0.224	0.167	0.053	0.027	0.008
A3	0.175	0.235	0.122	0.036	-0.036
A4	0.193	0.172	0.040	0.017	-0.001
A5	0.311	0.111	0.029	0.096	0.067
A6	0.282	0.121	0.036	0.070	0.049
A7	0.285	0.112	0.023	0.073	0.056
A8	0.288	0.087	0.022	0.071	0.062
A9	0.233	0.134	0.041	0.037	0.024
A10	0.203	0.224	0.138	0.062	-0.024
Table 13. Continued					
A11	0.169	0.244	0.117	0.014	-0.044
A12	0.233	0.134	0.027	0.037	0.027
A13	0.340	0.041	0.016	0.110	0.098

The ranking of alternatives is based on their dC_i values. A smaller dC_i value indicates that the alternative option is better. The ranking results of the alternatives calculated by the COBRA method are listed in Table 14, together with the company names and BIST codes.

Table 14. 2023 Ranking Results of Alternatives

Alternatives	Rank	BIST Code	Company Name
A1	1	AKCNS	Akçansa Çimento Sanayi ve Ticaret A.Ş.
A2	6	AKSA	Aksa Akrilik Kimya Sanayii A.Ş.
A3	3	CCOLA	Coca-Cola İçecek A.Ş.
A4	5	CIMSA	Çimsa Çimento Sanayi ve Ticaret A.Ş.
A5	12	EREGL	Ereğli Demir ve Çelik Fabrikaları T.A.Ş.
A6	9	ISDMR	İskenderun Demir ve Çelik A.Ş.
A7	10	KRDMD	Kardemir Karabük Demir Çelik Sanayi ve Ticaret A.Ş.
A8	11	OTKAR	Otokar Otomotiv ve Savunma Sanayi A.Ş.
A9	7	PETKM	Petkim Petrokimya Holding A.Ş.
A10	4	SASA	Sasa Polyester Sanayi A.Ş.
A11	2	TUPRS	Tüpraş-Türkiye Petrol Rafinerileri A.Ş.
A12	8	VESBE	Vestel Beyaz Eşya Sanayi ve Ticaret A.Ş.
A13	13	VESTL	Vestel Elektronik Sanayi ve Ticaret A.Ş.

When the financial performance ranking of the companies in 2023 is analysed in Table 14, the company with the highest financial performance is Akçansa Çimento Sanayi ve Ticaret A.Ş., and the company with the lowest financial performance is Vestel Elektronik Sanayi ve Ticaret A.Ş. In order to avoid excessive density and potential confusion in the tables, and to ensure that the analysis can be more easily followed by readers, the detailed calculation steps are provided only for the year 2023. The same procedures were applied to the remaining years, and the dC_i values together with the ranking results for all years are presented in Table 15.

Table 15. Comparative Results for 2018-2023

	2018		2019		2020	
	dC_i	Rank	dC_i	Rank	dC_i	Rank
AKCNS	0.038	7	0.069	9	0.052	9
AKSA	0.068	12	0.054	8	0.016	7
CCOLA	0.049	9	0.024	7	0.010	4
CIMSA	0.063	10	0.107	11	0.056	10
EREGL	-0.041	2	0.005	5	0.012	5
ISDMR	-0.093	1	-0.038	2	-0.049	3
KRDMD	0.040	8	0.118	13	0.138	13
OTKAR	0.067	11	-0.020	3	-0.074	2
PETKM	0.034	6	0.023	6	0.013	6
SASA	-0.023	3	-0.088	1	0.095	12
TUPRS	0.017	5	0.079	10	0.085	11
VESBE	0.010	4	-0.007	4	-0.088	1
VESTL	0.106	13	0.110	12	0.046	8
	2021		2022		2023	
	dC_i	Rank	dC_i	Rank	dC_i	Rank
AKCNS	0.064	10	-0.006	5	-0.047	1
AKSA	-0.041	7	-0.036	2	0.008	6
CCOLA	0.064	9	0.037	9	-0.036	3
CIMSA	-0.223	2	-0.112	1	-0.001	5
EREGL	-0.152	5	-0.005	6	0.067	12
ISDMR	-0.073	6	0.005	7	0.049	9
KRDMD	-0.239	1	0.076	11	0.056	10
OTKAR	-0.167	3	0.071	10	0.062	11
PETKM	-0.166	4	0.027	8	0.024	7
SASA	0.294	13	-0.006	4	-0.024	4
TUPRS	0.212	12	-0.015	3	-0.044	2
VESBE	0.036	8	0.092	12	0.027	8
VESTL	0.155	11	0.133	13	0.098	13

According to Table 15, the financial performance rankings of the companies vary between the years examined. In 2018, the top three companies with the best financial performance were ISDMR, EREGL and SASA showed the highest financial performance, while the companies with the lowest financial performance were VESTL, AKSA, and OTKAR, respectively. In 2019, the top three companies with the best financial performance were SASA, ISDMR, and OTKAR, while the lowest performing companies were KRDMMD, VESTL, and CIMS A. In 2020, the three companies with the highest financial performance were VESBE, OTKAR, and ISDMR, while the companies with the lowest financial performance were KRDMMD, SASA, and TUPRS. In 2021, the companies with the best financial performance were KRDMMD, CIMS A, and OTKAR, while the lowest ones were SASA, TUPRS, and VESTL. In 2022, CIMS A, AKSA, and TUPRS had the best performance, while the companies with the lowest financial performance were VESTL, VESBE, and KRDMMD. Finally, in 2023, AKCNS, TUPRS, and CCOLA are the companies with the highest financial performance, while VESTL, EREGL, and OTKAR are the companies with the lowest financial performance. The change in the financial performance rankings of companies between 2018 and 2023 is presented in Chart 1. This period range is important for understanding the performance fluctuations of companies because it includes the period before and after the COVID-19 pandemic.

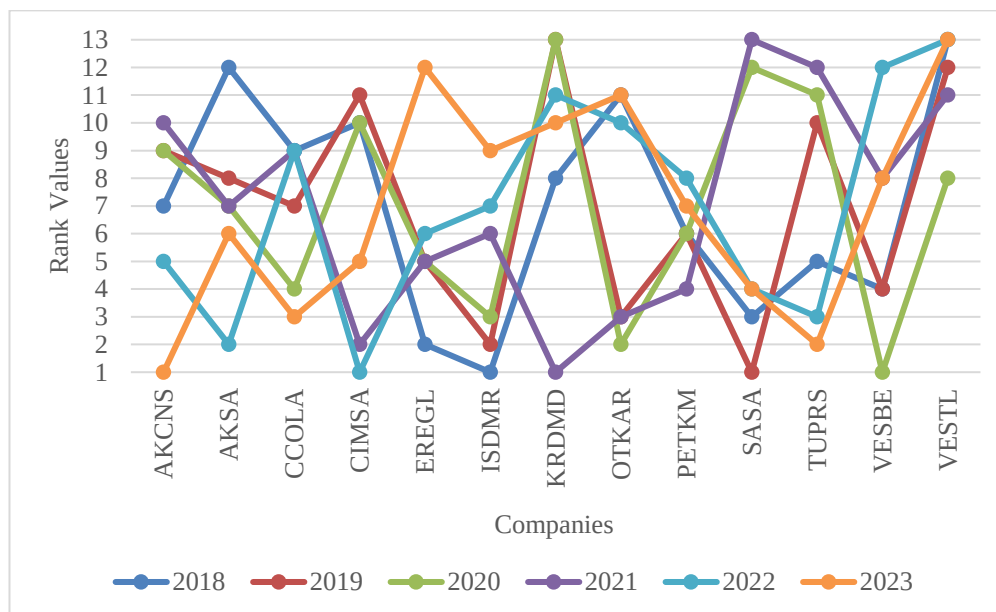


Chart 1. Change in Financial Performance Rankings of Companies in 2018-2023

According to Chart 1, when we look at the processes before and after the COVID-19 pandemic, ISDMR and SASA were the top three companies with the best financial performance ranking in 2018 and 2019 before the pandemic, while OTKAR in 2020 and 2021 during the pandemic, and TUPRS in 2022-2023 after the pandemic.

5. Sensitivity Analysis

Sensitivity analysis helps analyze the effect of changes in criteria data by comparing different scenarios, and the results obtained from these scenarios according to changing conditions (Goodridge, 2016: 27). With sensitivity analysis, the strength of the model can be measured by examining the effect of changes in input data on the results obtained with multi-criteria models

(Karande et al., 2016: 406). In the literature, different techniques are used during the sensitivity analysis stage of MCDM studies (Demir et al., 2024). In this study, sensitivity analyses were carried out based on the comparison of the results obtained from different MCDM techniques, as it is a preferred approach in the literature (Badi et al., 2023; Bonab et al., 2023; Liu et al., 2023). Firstly, the consistency of the results obtained from the COBRA method, which is the ranking model of the study, was tested. The rankings obtained from the MEREC-COBRA integrated model were compared with the rankings obtained from different MCDM methods. In this comparison, Spearman's rank correlation coefficient (r_s) was employed to assess the consistency between the results. At this stage, the MEREC method was used for weighing the criteria, and the results are shown in Table 16.

Table 16. Ranking Results Obtained with MEREC Weighted Different MCDM Methods

	2018					2019				
	COBRA	EDAS	ARAS	COCOSO	WASPAS	COBRA	EDAS	ARAS	COCOSO	WASPAS
A1	7	5	7	7	6	9	9	9	8	9
A2	12	10	10	10	10	8	8	8	9	8
A3	9	9	9	9	9	7	6	6	4	6
A4	10	11	11	12	11	11	11	11	11	13
A5	2	2	2	2	2	5	3	3	2	3
A6	1	1	1	1	1	2	1	2	1	1
A7	8	7	8	8	8	13	12	12	12	12
A8	11	12	12	11	12	3	4	4	7	5
A9	6	6	6	6	5	6	7	7	5	7
A10	3	3	3	3	3	1	2	1	6	2
A11	5	8	5	5	7	10	10	10	10	10
A12	4	4	4	4	4	4	5	5	3	4
A13	13	13	13	13	13	12	13	13	13	11
r_s	-	0.945	0.984	0.978	0.967	-	0.967	0.973	0.819	0.951
	2020					2021				
	COBRA	EDAS	ARAS	COCOSO	WASPAS	COBRA	EDAS	ARAS	COCOSO	WASPAS
A1	9	8	8	8	8	10	10	10	10	10
A2	7	7	7	7	7	7	7	7	7	7
A3	4	5	5	5	5	9	9	9	9	9
A4	10	10	10	10	10	2	2	2	2	2
A5	5	4	4	4	4	5	4	4	4	4
A6	3	1	1	1	1	6	6	6	6	6
A7	13	13	13	13	13	1	1	1	1	1
A8	2	3	3	3	3	3	5	5	5	5
A9	6	6	6	6	6	4	3	3	3	3
A10	12	12	12	12	12	13	13	13	13	13
A11	11	11	11	11	11	12	12	12	12	12
A12	1	2	2	2	2	8	8	8	8	8
A13	8	9	9	9	9	11	11	11	11	11
r_s	-	0.973	0.973	0.973	0.973	-	0.984	0.984	0.984	0.984
	2022					2023				
	COBRA	EDAS	ARAS	COCOSO	WASPAS	COBRA	EDAS	ARAS	COCOSO	WASPAS
A1	5	5	5	6	4	1	1	1	1	1
A2	2	2	2	3	2	6	6	6	5	5
A3	9	9	9	8	9	3	3	3	3	3
A4	1	1	1	1	1	5	5	5	4	4
A5	6	4	4	4	5	12	12	12	11	12
A6	7	6	6	5	6	9	9	9	9	9
A7	11	10	10	10	10	10	10	10	10	10
A8	10	11	11	12	11	11	11	11	12	11
A9	8	8	8	7	7	7	7	7	8	8
A10	4	7	7	9	8	4	4	4	7	6
A11	3	3	3	2	3	2	2	2	2	2
A12	12	12	12	11	12	8	8	8	6	7
A13	13	13	13	13	13	13	13	13	13	13
r_s	-	0.956	0.956	0.879	0.940	-	1.000	1.000	0.951	0.978

According to Table 16, the ranking results obtained by applying the criteria weights found by the MEREC method to different MCDM methods displayed small deviations, for each year considered. For the years 2020 and 2021, the rankings obtained with the EDAS, ARAS, COCOSO, and WASPAS methods were the same, while the rankings obtained with the EDAS and ARAS methods in 2022, and the COBRA, EDAS, and ARAS methods in 2023, were the same. The Spearman correlation coefficient being greater than 0.8 between 2018 and 2023 indicates that there is a high positive relationship between COBRA and other MCDM methods. Thus, it can be concluded that the proposed approach provides results consistent with other ranking methods.

In the second stage, the consistency of the weights obtained from the MEREC method, which is the criterion weighting model of the study, was analyzed. In this stage, where the COBRA approach was used as the ranking method, the effect of different weighting methods on the result was investigated and the findings are presented in Table 17.

Table 17. COBRA Method Rankings Obtained with Different Weighting Methods

Year	2018						2019					
	MEREC	ENTROPY	CRITIC	SD	CILOS	EQUAL WEIGHTING	MEREC	ENTROPY	CRITIC	SD	CILOS	EQUAL WEIGHTING
A1	7	6	8	8	8	8	9	9	7	9	9	9
A2	12	11	9	11	12	11	8	8	10	10	10	10
A3	9	9	7	7	10	7	7	6	3	4	5	6
A4	10	10	10	12	11	12	11	11	11	11	11	11
A5	2	2	4	2	3	2	5	3	8	5	7	2
A6	1	1	2	1	1	1	2	2	5	1	1	1
A7	8	5	11	9	7	9	13	12	13	13	13	13
A8	11	12	12	10	9	10	3	4	9	8	8	7
A9	6	8	5	6	6	6	6	7	2	3	4	5
A10	3	3	6	3	2	3	1	1	6	6	3	4
A11	5	7	1	4	5	4	10	10	4	7	6	8
A12	4	4	3	5	4	5	4	5	1	2	2	3
A13	13	13	13	13	13	13	12	13	12	12	12	12
r_s	-	0.945	0.846	0.962	0.973	0.962	-	0.973	0.549	0.764	0.819	0.874

Table 17. Continued

Year	2020						2021					
	MEREC	ENTROPY	CRITIC	SD	CILOS	EQUAL WEIGHTING	MEREC	ENTROPY	CRITIC	SD	CILOS	EQUAL WEIGHTING
A1	9	7	5	7	8	7	10	10	11	11	10	11
A2	7	8	9	8	7	8	7	8	9	9	8	9
A3	4	5	3	4	5	5	9	7	8	6	9	7
A4	10	9	10	9	10	10	2	3	2	4	5	4
A5	5	2	6	5	6	3	5	1	6	3	3	3
A6	3	1	4	1	2	1	6	2	3	2	4	2
A7	13	13	13	13	13	13	1	5	4	5	2	5
A8	2	4	7	6	3	6	3	6	10	7	6	6
A9	6	6	2	3	4	4	4	4	1	1	1	1
A10	12	12	12	12	12	12	13	13	13	13	13	13
A11	11	11	8	10	11	9	12	11	7	10	11	10
A12	1	3	1	2	1	2	8	9	5	8	7	8
A13	8	10	11	11	9	11	11	12	12	12	12	12
r_s	-	0.912	0.775	0.874	0.973	0.868	-	0.819	0.676	0.769	0.890	0.802
Year	2022						2023					
	MEREC	ENTROPY	CRITIC	SD	CILOS	EQUAL WEIGHTING	MEREC	ENTROPY	CRITIC	SD	CILOS	EQUAL WEIGHTING
A1	5	7	6	6	8	6	1	3	2	2	1	2
A2	2	2	3	3	6	3	6	7	6	5	5	5
A3	9	9	8	8	3	8	3	2	3	3	3	3
A4	1	1	1	1	4	1	5	5	5	4	4	4
A5	6	3	4	4	2	4	12	12	11	11	7	11
A6	7	4	5	5	5	5	9	10	9	9	6	9
A7	11	10	10	10	9	10	10	11	10	10	8	10
A8	10	11	12	12	10	12	11	9	12	12	10	12
A9	8	8	7	7	7	7	7	6	7	7	12	8
A10	4	6	9	9	12	9	4	1	4	6	11	6
A11	3	5	2	2	1	2	2	4	1	1	2	1
A12	12	12	11	11	11	11	8	8	8	8	9	7
A13	13	13	13	13	13	13	13	13	13	13	13	13
r_s	-	0.912	0.879	0.879	0.549	0.879	-	0.929	0.989	0.973	0.681	0.967

According to Table 17, the COBRA method rankings obtained with six different weighting methods together with the MEREC method differed on a yearly basis. In 2018, the ranking results obtained with SD and Equal Weighting methods were the same, while in 2022, the rankings obtained with CRITIC, SD, and Equal Weighting methods were the same. In Table 17, the consistency of the rankings obtained through the COBRA method with different weighting schemes is assessed using Spearman's rank correlation coefficients (r_s). The majority of the coefficients are above 0.8, suggesting that the rankings generated by alternative weighting approaches are strongly and positively correlated.

6. Discussion and Conclusion

In this study, the financial performance of 13 companies operating in the manufacturing sector and included in the BIST Participation Sustainability Index between 2018 and 2023 was evaluated using MCDM methods. The selection of the manufacturing sector was influenced by the presence of companies in the relevant index. In the analysis of the study, eight financial ratios under the four main headings of liquidity, financial structure, activity, and profitability ratios were used as criteria. Data on these criteria were obtained from the Public Disclosure Platform. The MEREC method was utilized to determine the importance weights of the criteria. When the criterion weights are analyzed, it is observed that the highest criterion weight belongs to the net profit margin for 2018 and the return on assets ratio for 2019-2023. It is understood that profitability ratios are the most effective ratios in determining the financial performance of manufacturing sector companies. The financial leverage ratio was the lowest criterion weight among the financial structure ratios, analyzed over all years. After determining the criterion weights, the performance ranking of the companies was conducted using the COBRA method. It was observed that the ranking results obtained with the MEREC-COBRA model varied over the years. In 2018, the company with the highest financial performance was found to be ISDMR, SASA in 2019, VESBE in 2020, KRDMMD in 2021, CIMS A in 2022, and AKCNS in 2023. When the literature on financial performance measurement is examined, limited studies on the companies included in the BIST Participation Sustainability Index are observed. Among the known studies, Kılıçarslan (2022) evaluated the financial performance of all companies registered in the index for the years 2016-2021 with the help of the Bulut Index and the Aras methods, using 12 financial ratios. In another study by Güçlü and Göktaş (2023), 10 financial ratios were used with the data obtained from the 2022 year-end financial statements of 11 manufacturing sector companies included in the relevant index. Criteria weights were determined by using the entropy method, and the results obtained by ranking the alternatives using the Probability Evaluation System (PES) and TOPSIS methods were compared. The financial performance ranking obtained as a result of the PES method is as follows: AKSA, TUPRS, SUNTK, AKCNS, ISDMR, EREGL, PNSUT, KRDMMD, KARSN, VESBE, VESTL. According to the TOPSIS method results, the financial performance ranking is AKSA, TUPRS, SUNTK, AKCNS, EREGL, ISDMR, KRDMMD, PNSUT, KARSN, VESBE, and VESTL. This study, unlike the study of Güçlü and Göktaş (2023), as of September 2024, the financial performance of 13 manufacturing companies included in the BIST Participation Sustainability Index between 2018-2023 in terms of the COVID-19 Pandemic processes. As a method, in Güçlü and Göktaş (2023), the Entropy method was used to calculate the criteria weights, and the PES and TOPSIS methods were used to rank the alternatives, and the ranking results obtained were compared. In this study, the newly introduced MEREC and COBRA methods were used. Criterion weights were determined by the MEREC method, and alternatives were ranked by the COBRA method. In addition, to measure the validity and robustness of the model proposed in the study, a two-stage sensitivity analysis was performed to compare the results obtained from different methods. Firstly, the results obtained with the COBRA method were compared with the results obtained from different MCDM methods (EDAS, ARAS, COCOSO, WASPAS) used in ranking the alternatives. Then, in order to measure the strength of the related model, the results obtained by using the criteria weights from the MEREC method were compared with the results obtained from different MCDM methods (Entropy, CRITIC, SD, CILOS, Equal Weighting) used in criteria weighting. In general, small differences were observed in the rankings obtained in these two stages. The Spearman's correlation test was performed to determine the

relationship between the rankings. According to the results of this test, high positive relationships were observed between the rankings, and the suitability of the model used in the study was also determined.

It is believed that the outputs of the study have important implications for the firms included in the analysis and investors. In addition to allowing firms to compare their performances with those of other firms, it enables managers to monitor the course of certain financial ratios over the years. It provides an idea for taking necessary precautions and corrective measures. For investors, it provides decision support in investment planning for the relevant index. In the related literature, it is emphasized that the index is suitable for an investor profile with high Islamic sensitivity, and the expansion rate of the index is an issue that should not be ignored. The findings were not only compared with the existing literature but also evaluated in the context of Turkey's recent macroeconomic conditions and sectoral dynamics. For instance, in 2020, disruptions in production and supply chains due to the COVID-19 pandemic negatively affected the financial performance of certain firms. In 2021 and 2022, the sharp rise in energy costs led to declines in profitability ratios, particularly for companies operating in energy-intensive industries. Exchange rate fluctuations directly influenced the performance of firms with high dependence on imported inputs or those oriented toward exports. Moreover, inflationary pressures strained firms' financial structures, while favoring those with strong cash flows. In this context, the performance rankings reflect not only the internal dynamics of firms but also the impact of macroeconomic conditions and sector-specific characteristics. However, the most important limitation of the study is the range of years subject to analysis and the criteria used, which are based on financial ratios. It should be kept in mind that different performance rankings may be obtained when different sets of criteria are used.

The most significant implication for managers is that profitability ratios emerged as the key determinant of corporate performance during the 2019–2023 period. In particular, the fact that return on assets carried the highest criterion weight indicates that managers should design their financial strategies around the efficient utilization of assets and the sustainability of profitability. Accordingly, cost control, productivity-enhancing investments, and innovative business models that support profitability stand out as priority strategic areas. From the investors' perspective, the finding that the highest-performing companies varied across years is particularly critical. The prominence of ISDMR in 2018, SASA in 2019, VESBE in 2020, KRDMD in 2021, ÇİMSA in 2022, and AKCNS in 2023 demonstrates that different sub-sectors of the manufacturing industry (e.g., iron and steel, chemicals, and cement) exhibited strong performances at different times, particularly during and after the pandemic. This suggests that, rather than focusing on a single company or sub-sector, investment decisions should be guided by flexible and diversified portfolio strategies that take into account period-specific trends and sectoral dynamics.

The findings of the study demonstrate the effectiveness of multi-criteria decision-making approaches in financial performance analysis. In this context, for companies in the manufacturing sector to gain a sustainable competitive advantage, the use of these methods in financial performance management and their integration into corporate decision-making processes are crucial. Identifying financial strategies aligned with sustainability principles and, in this regard, developing performance-based incentive systems by policymakers will enhance firms' competitive power. The integrated MEREC-COBRA approach, the main model of the study, is proposed as an applicable model for optimizing decision-making processes of policymakers.

For future studies, since the BIST Participation Sustainability Index is a new index and there are very few studies on it in the literature, the financial performances of companies operating in different sectors can be examined. In addition, financial ratios can be diversified, and new studies can be carried out using different MCDM methods in the literature. In this study, objective MCDM techniques were used both in determining the criteria weights and in performance rankings. The results can be compared with the studies conducted using subjective methods.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There is no potential conflicts of interest in this study.

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THE IMPACT OF ESG CONTROVERSIES ON THE MARKET VALUE IN THE ENERGY SECTOR

Enerji Sektöründe ESG (ÇSY) Tartışmalarının Piyasa Değeri Üzerindeki Etkisi

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Abstract

The energy sector has relatively higher exposure to scandals and controversial publicity due to the nature of industry operations. Thus, this study focuses on the energy sector to evaluate the impact of ESG (Environmental, Social and Governance) controversy scores of LSEG database on market value of firms. We investigate the relationship between ESG controversies and the market value of 393 firms using annual data from 2013 to 2022 through Dynamic Panel Data system GMM Regression Models. The findings of the study reveal that the market value of firms in the previous period has had a statistically significant positive effect on the market value of firms in the current period. Our analysis reveals a positive and statistically significant association between Governance Controversy scores and market value. Our findings suggest governance controversies have the most direct and measurable impact on firm value in the energy sector, possibly due to their stronger influence on operational performance and investor confidence. Implications of the study may help investors and policymakers to make decisions that prioritize ESG considerations in the energy sector as firms with fewer governance controversies are rewarded by investors with higher valuations.

Öz

Enerji sektörü, faaliyetlerinin doğası gereği skandallar ve tartışmalı kamuoyu ilgisine diğer sektörlere göre daha fazla maruz kalmaktadır. Bu nedenle, bu çalışma enerji sektörüne odaklanarak LSEG veri tabanındaki ESG (Çevresel, Sosyal ve Yönetişim) tartışma puanlarının firmaların piyasa değeri üzerindeki etkisini değerlendirmeyi amaçlamaktadır. 2013-2022 dönemine ait yıllık veriler kullanılarak 393 firma üzerinde ESG tartışmaları ile piyasa değeri arasındaki ilişki, Dinamik Panel Veri (Sistem GMM) regresyon modeli aracılığıyla incelenmiştir. Çalışmanın bulguları, bir önceki dönemdeki firma piyasa değerinin mevcut dönemdeki piyasa değeri üzerinde istatistiksel olarak anlamlı ve pozitif bir etkisi olduğunu göstermektedir. Analiz sonuçları, yönetim tartışmaları puanları ile piyasa değeri arasında pozitif ve istatistiksel olarak anlamlı bir ilişki bulunduğunu ortaya koymaktadır. Bulgular, yönetim tartışmalarının enerji sektöründe firma değeri üzerinde en doğrudan ve ölçülebilir etkiye sahip olduğunu, bunun da operasyonel performans ve yatırımcı güveni üzerindeki daha güçlü etkilerinden kaynaklanabileceğini göstermektedir. Çalışmanın sonuçları, enerji sektöründe ESG unsurlarını önceliklendiren kararların alınmasına yardımcı olabilir. Zira daha az yönetim tartışmasına sahip firmalar, yatırımcılar tarafından daha yüksek değerlemelerle ödüllendirilmektedir.

Keywords:

Social
Controversies,
Governance
Controversies,
Market Value,
Energy Sector.

JEL Codes:

Q56, G34, O16.

Anahtar

Kelimeler:

Sosyal Tartışmalar,
Yönetişim
Tartışmaları,
Piyasa Değeri,
Enerji Sektörü.

JEL Kodları:

Q56, G34, O16.

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1. Introduction

Many dramatic business scandals have shaken the corporate world throughout history. Especially in recent decades, several important corporate controversies such as Enron, HealthSouth, Parmalat, Shell, Siemens AG, Tyco, and WorldCom have generated extensive consequences on various stakeholders (Mercedes, 2022). These consequences include diminished goodwill of the company, lowered market value, and escalated business risks, as controversies lead to weakened corporate reputation through negative media reporting (Kim et al., 2014). Controversies can be categorized as environmental, social, or governance (ESG) controversies as they differ in their nature. For instance, toxic waste spills are considered environmental controversies, while human-rights violations are classified as social controversies, and accounting frauds are categorized as governance-related controversies (Nugent et al., 2021). Environmental controversies have gained significant attention as climate crises induce stakeholders to prefer eco-friendly companies. Indeed, negative environmental news can harm corporate reputation, impact divestment campaigns, and lead to significant stock value declines. For example, the Italian luxury brand Moncler experienced a 6% market value drop when the exploitation of geese was exposed in the media (Capelle-Blancard and Petit, 2019). Therefore, corporate controversies and their consequences have emerged as a hot subject for investors and researchers.

There is clear evidence that controversial industries have a higher level of business risk than uncontroversial industries because of the sinful or controversial nature of their products or services, which directly or indirectly harm consumers, society, and the environment (Jo and Park, 2020). There are two types of industries that can be classified as controversial: (1) sinful industries (tobacco, gambling, and alcohol) and (2) industries involved in environmental, social, and ethical/moral issues (oil and gas, mining, wastage, and defense-related weapons) (Jo and Park, 2020). Similarly, an industry that provides controversial products or services or an industry engaging in controversial conduct in achieving business objectives can be defined as a controversial industry (Yoon et al., 2006; Hong and Kacperczyk, 2009; Cai et al., 2012). In particular, the energy sector has high exposure to controversial publicity due to the nature of industry operations. It is important to look at some historical examples. The Deepwater Horizon oil spill in April 2010 is an important case. Three months after the incident, BP (formerly The British Petroleum Company plc and BP Amoco plc) had lost fifty percent of its share value or tens of billions of dollars. Some even claimed that, due to the size of the corporation, the oil leak affected the whole British economy (Smith et al., 2011). The March 2011 nuclear tragedy at Fukushima Daiichi is an important case in the nuclear energy industry. Although the nuclear accident directly resulted from the Great East Japan Earthquake, it became more severe due to governance failures by TEPCO (Tokyo Electric Power Company). As a result of the accident, the stock price of the company plummeted (Kawashima and Takeda, 2012). To maintain the social commitment and legitimacy towards the community, substantial policies have been implemented in the energy sector, such as gas emissions reduction, investments in renewable energy alternatives, community development programs to build schools and hospitals, and youth employment projects (Frynas, 2009). The energy sector has relatively higher exposure to controversial publicity due to the nature of industry operations. For this reason, this study focuses on the energy sector and aims to evaluate the impact of ESG controversies scores (Environmental Controversies, Social Controversies, and Governance Controversies) of the LSEG (former Refinitiv EIKON) database on the market value of firms. Thus, this study focuses on the market value of firms in the energy sector.

Since ESG controversies can negatively impact a company's reputation and financial health, understanding the relationship between ESG controversies and market performance may help investors and policymakers to make decisions that prioritize ESG considerations in the energy sector. This study attempts to fill the research gap as there is no clear consensus regarding the impacts of ESG Controversies on the market value of firms, and it may contribute to the existing literature since it is one of the first studies which explore the potential impacts of different dimensions of ESG controversies (environmental, social, and governance), to the best of our knowledge. In addition, the study may provide a better comprehension of the financial impacts of ESG controversies for business managers in the energy sector to help them make effective decisions about their operations and formulate better reputation management strategies to generate value. The rest of the paper is structured as follows. Section 2 presents the theoretical background and review of empirical studies. Section 3 explains the data and methodology used in this study. Section 4 displays the findings, and Section 5 concludes the study.

2. Theoretical Background and Review of Empirical Studies

This study is built on two theories: “Signaling Theory” and “Stakeholder Theory”. These theories deliver a vigorous framework for understanding how corporate controversies may impact firm performance and stakeholder engagement, especially for the firms operating in the energy sector.

Signaling Theory argues that when there is an information asymmetry, one party (the sender) sends information to another party (the receiver) through signals. In the context of corporate governance, firms use different types of signals to communicate their commitment to sustainability to their stakeholders. This theory stresses the importance of engaging with stakeholders for decision-making processes, especially tackling controversial concerns. According to signaling theory, firms that actively disclose their ESG activities propagate positive signals to stakeholders, strengthening corporate reputation and reducing the negative impacts of related controversies (Eccles et al., 2014; Lins et al., 2017). Similarly, stakeholder theory emphasizes that maintaining a social license to operate is crucial, as firms that surpass ESG performance can strengthen stakeholder trust and value creation. Companies that engage productively with their stakeholders can continue a sustainable long-term legitimacy, which eventually can reduce the harm created by various corporate controversies (Curran, 2017; Hoffmann and Kristensen, 2017).

Corporate controversies come with higher penalties, which impact various stakeholders (Warner, 1977; Zavgren, 1983; Jones, 1987; Davidson III and Worrel, 1988; Zahra et al., 2005; Cole et al., 2021). In fact, Nirino et al. (2021) found that ESG controversies negatively affect financial performance, while Dogru et al. (2022) noted that the impacts of ESG controversies are increased during external shocks like the COVID-19 pandemic. Although various studies have focused on the relationship between ESG on the market value of firms (e.g., Duque-Grisales and Aguilera-Caracuel, 2021; Ademi and Klungseth, 2022; Chouaibi et al., 2022; Saygili et al., 2022; Chung et al., 2023; Korkmaz and Nur, 2023), studies examining the relationship between ESG-related controversies and market value are less in number. However, there are few attempts to explore the impacts of corruption and scandals on various measures of financial performance and market value. Most of these studies have reported negative impacts, especially for different stakeholders, including employees, business partners, investors, creditors, auditors, regulators,

capital markets, and society at large (e.g., Zahra et al., 2005; Cole et al., 2021; La Rosa and Bernini, 2022; Agnese et al., 2023; Ma and Ma, 2025). For example, La Rosa and Bernini (2022) investigated listed companies in Europe in 2009–2019 and found that ESG controversies, especially environmental controversies, heighten the cost of equity capital. Similarly, Agnese et al. (2023) examined European banks from 2005 to 2019 and found that prior instances of ESG controversies affect current levels of such controversies. Ma and Ma (2025) detected Chinese A-share firms during 2010–2020 and proposed that ESG controversies negatively influence firm value through lower levels of green innovation, total factor productivity, and financing constraints. Yet, the single-country setting restricts the generalizability of their findings. Interestingly, a few studies reported positive impacts of ESG controversies on firm value (e.g., Aouadi and Marsat, 2018; Melinda and Wardhani, 2020). Aouadi and Marsat (2018) analyzed more than 4000 firms from 58 countries during 2002–2011 and observed that ESG controversies are related to greater firm value for high-attention firms. Similarly, Melinda and Wardhani (2020) studied 1,356 companies from 22 countries in Asia during 2014 to 2018 and found that ESG controversies are positively related to company value due to the positive signal delivered about transparency and accountability inclination.

In short, previous literature shows mixed and non-conclusive evidence regarding the relationship between ESG controversies and firm value. Moreover, relatively fewer attempts were made to analyze the energy sector, which is fundamentally more exposed to ESG-related controversies due to the nature of its operations. Unlike earlier studies that either adopt a cross-industry approach or a country-specific setting, our study isolates the energy sector, which is one of the most controversy-prone industries, and applies a dynamic panel GMM estimator to capture the persistence of firm value and mitigate endogeneity concerns. Furthermore, many prior analyses are limited by shorter time spans or regional restrictions, which constrain the generalizability of their findings. Hence, this study aims to address these gaps by examining a global sample of 393 energy firms across 54 countries over the period 2013–2022. Most importantly, by analyzing the disaggregated ESG Controversy Scores obtained from LSEG (Refinitiv Eikon), which are categorized into environmental, social, and governance dimensions, our study offers new insights into the energy sector. It reveals which specific types of controversies have the most significant impact on firm value.

3. Data and Methodology

The sample of the study consists of 393 firms operating in the energy sector, collected from the LSEG (formerly Refinitiv EIKON) database. Firm selection was based on the operating industry. If a firm operated in one or more of the industries of Coal, Oil & Gas, Oil & Gas Related Equipment and Services, Renewable Energy, and Uranium, it was added to the sample. The sample covers 54 countries during the period of 2013–2022. These years were selected based on data availability and consistency in ESG controversies reporting. Prior to 2013, data for ESG controversies were less and inconsistent across firms and regions. The ESG controversies scores used in this study are Environmental Controversies (CE), Social Controversies (CS), and Governance Controversies (CG) Scores. These scores are based on 23 ESG controversy topics and reflect the controversies report available in various media. Each score ranges from 0 to 100, where a score of 100 indicates no reported controversies, while a score of 0 reflects a higher number or severity of incidents, which implies the media reported various violations and

allegations regarding bad corporate practices on ESG. The scores are interval-scaled and benchmarked by industry groups to ensure comparability.

In the study, the logarithm of the Market Capitalization of Companies (LogMCap) operating in the energy sector was used as the dependent variable to represent market value. As independent variables: logarithm of the lag of one period of the dependent variable (LogMCap(-1)), as well as the dimensions of ESG controversies CE, CS, and CG were used. Several financial performance ratios i.e. Return on Asset (ROA) as a proxy of profitability, Current Ratio (CR) as a proxy of liquidity, Total Asset to Total Equity (TATE) as a proxy of financial leverage, Asset Turnover (AT) as a proxy of efficiency as well as logarithm of Revenue from Business Activities (LogTR) as a proxy of size were used as control variables. The list of the variables used in the study is given in Table 1 below.

Table 1. Variable Definitions

Variable	Abbreviation	Definition
Logarithm of the Market Capitalization	LogMCap	Total market value of all applicable types of shares issued by a company.
Environmental Controversies	CE	Environmental score, which is an overall company score based on negative media coverage linked to environmental controversies.
Social Controversies	CS	Social controversies score, which includes negative media attention regarding a company's ability to establish and maintain trust and loyalty among its employees, customers, and broader society.
Governance Controversies	CG	Governance controversies score reflects the negative media publicity regarding board members/ executives' actions, and about the function of the board that affects the interest & wealth of the shareholders.
Return on Asset	ROA	Pre-tax return on assets highlights the efficiency of operations in generating profit.
Current Ratio	CR	Current asset/current liabilities
Total Asset to Total Equity	TATE	Total Assets / Total Equity
Logarithm of Revenue from Business Activities	LogTR	Total revenues represent revenues from all of a company's operating activities.
Asset Turnover	AT	Net Sales (or Revenue) / Average Total Assets

The Stata 15 program was used in the analysis of the study. Descriptive statistics for the variables are given in Table 2.

Table 2. Descriptive Statistics

Variable	Obs.	Mean	Std.Dev.	Min.	Max.
LogMCap	4,131	9.263	.866	4.125	12.363
CE	3,053	50.515	13.645	0	55.71
CS	3,053	54.605	4.436	0	58.14
CG	3,053	52.068	5.377	30.906	60.262
ROA	2,963	.0324	.126	-4.764	.995
CR	4,336	2.494	34.917	0	2291.02
TATE	4,199	3.167	11.753	1	616.75
LogTR	4,280	9.215	.933	4.41	11.78
AT	4,226	.786	.942	0	12.05

In econometric analysis, to avoid the problem of multicollinearity between independent variables, first, a correlation matrix is created, and if there are independent variables that are highly correlated (0.80 or above), some of them should be excluded from the model. Correlation analysis is often performed to examine whether there is a high level of relationship between independent variables, yet occasionally the dependent variable may also be included to see the relationships between independent variables and the dependent variable. Correlation analysis results are given in Table 3.

Table 3. Correlation Analysis Results

	LogMCap	CE	CS	CG	ROA	CR	TATE	LogTR	AT
LogMCap	1.000								
CE	-0.321 [0.000]	1.000							
CS	-0.275 [0.000]	0.313 [0.000]	1.000						
CG	-0.179 [0.000]	0.105 [0.000]	0.333 [0.000]	1.000					
ROA	0.232 [0.000]	-0.051 [0.012]	-0.029 [0.152]	-0.043 [0.036]	1.000				
CR	-0.004 [0.079]	0.060 [0.000]	0.041 [0.021]	0.057 [0.001]	0.000 [0.096]	1.000			
TATE	-0.059 [0.000]	0.006 [0.073]	-0.040 [0.027]	-0.028 [0.011]	-0.048 [0.008]	0.079 [0.000]	1.000		
LogTR	0.752 [0.000]	-0.324 [0.000]	-0.319 [0.000]	-0.239 [0.000]	0.179 [0.000]	-0.204 [0.000]	-0.013 [0.000]	1.000	
AT	0.048 [0.002]	-0.019 [0.028]	-0.022 [0.022]	0.018 [0.030]	0.148 [0.000]	-0.068 [0.000]	-0.000 [0.097]	0.345 [0.000]	1.000

Note: Values in parentheses show the significance level of the correlation relationship between variables.

When the correlation coefficients between the independent variables are examined, it is seen that there will be no multicollinearity problem in the model with these independent variables, since the correlation coefficients between the independent variables are below 0.80. In addition to correlation analysis, another analysis that can be used to identify independent variables that may cause multicollinearity among independent variables is VIF (Variance Inflation Factor) analysis. VIF analysis is performed solely on the independent variables, indicating that any independent variable with a central VIF value greater than 5 should be excluded from the analysis to avoid multicollinearity issues. The VIF analysis results for the independent variables used in the study are presented in Table 4.

Table 4. VIF Analysis Results

Variables	VIF	1/VIF
LogTR	1.65	0.606
CS	1.34	0.746
AT	1.23	0.810
CE	1.21	0.826
CG	1.20	0.834
CR	1.09	0.920
ROA	1.06	0.945
TATE	1.01	0.988
Mean VIF	1.22	

As seen in the table above, the central VIF values of the independent variables are less than 5. Therefore, there seems to be no multicollinearity problem in the model created by using the independent variables listed in Table 4.

To analyze the impact of ESG controversies on the market value of companies, the two-stage system GMM (Generalized Method of Moments) estimator was used. The two-stage system GMM is a dynamic panel data method developed by Arellano and Bover (1995) and Blundell and Bond (1998). The two-stage system GMM estimator considers the level equation as well as the difference equation and combines them within a “system”. There are two main GMM estimators: the GMM-difference estimator proposed by Arellano and Bond (1991) and the GMM-system estimator, which includes the Arellano and Bover (1995) method that uses differenced values of the dependent variable in the instrument matrix and the Blundell and Bond (1998) method (two-stage system GMM) that uses the original and differenced observations in the instrument matrix. This method provides consistent results that are resistant to autocorrelation, heteroscedasticity, and endogeneity problems in the analysis. System GMM estimator tends to perform better than the difference GMM estimator regarding finite sample bias and mean squared error, and coefficient estimator standard errors (Hacıoğlu, 2017). Although the two-stage system GMM and the difference GMM approaches are widely used in literature, the two-stage system GMM is usually preferred as it gives more reliable results when working with random variables (Roodman, 2009).

There are three basic conditions for the reliability of the system GMM estimator: Firstly, the GMM estimator must satisfy the condition of absence of the second-order autocorrelation of the error term. Since null hypotheses are defined as the absence of the first-order/second-order autocorrelation, the condition that the null hypothesis cannot be rejected or rejected in AR (1) and that the null hypothesis cannot be rejected in AR (2) depends on the validity of the appropriate diagnostic statistics. Secondly, in the system GMM, the number of instrumental variables should not exceed the number of observations, as it creates a large number of "weak" instrumental variables that may lead to biased predictions. In addition, if the probability value of the Hansen test statistic is greater than 0.05 or 0.10 (meaning the acceptance of the null hypothesis in terms of the validity of the overidentification constraints, indicating the suitability of the instrumental variables), it means that the instrumental variables are valid. In other words, the model is defined correctly. Under valid moment conditions, the Hansen test statistic asymptotically approaches the chi-square distribution. The last condition for the validity of System GMM is a requirement that the lagged value of the dependent variable, which is considered as the convergence indicator, should be less than one (Roodman, 2006)

The structure of the dynamic panel model based on the study is as follows:

$$y_{it} = \alpha y_{it-1} + \beta x_{it} + \varepsilon_{it} \quad (1)$$

In this equation, y_{it} defines the dependent variable, y_{it-1} defines a lag of the dependent variable, and x_{it} defines the other independent variables used in the study. ε_{it} represents the error term of the model.

The equation of the model is given below.

$$\begin{aligned} \text{LogMCapit} = & \beta_1 \text{LogMCapit}(-1) + \beta_2 \text{CEit} + \beta_3 \text{CSit} + \beta_4 \text{CGit} + \beta_5 \text{ROAit} \\ & + \beta_6 \text{CRit} + \beta_7 \text{TATE} + \beta_8 \text{LogTRit} + \beta_9 \text{ATit} + \varepsilon_{it} \end{aligned} \quad (2)$$

where, LogMCap: Logarithm of the Market Capitalization (firm value), CE: Environmental Controversies, CS: Social Controversies, CG: Governance Controversies, ROA: Return on Asset (profitability), CR: Current Ratio (liquidity), TATE: Total Asset to Total Equity (financial leverage), LogTR : Logarithm of Revenue from Business Activities (firm size), AT: Asset Turnover (efficiency).

This study utilized market capitalization as a measure of firm value as the primary dependent variable since it reflects investors’ perceptions of a company’s financial performance and future directions. There are also a few control variables that are constantly used in the literature. We employed return on assets, current ratio, total assets to total equity, revenue from business activities, and asset turnover as control variables. Return on Assets (ROA) provides essential information about the quality of management and operational efficiency of the company and is one of the key variables to consider, which may influence market value. The current ratio (CR) is an essential indicator of financial stability and risk level for investors, and it can indirectly affect market value through liquidity problems. The total assets to total equity (TATE) ratio was included as it reflects the company’s financial leverage level. Financial leverage has a direct impact on the market value of firms because if the debt is not used effectively, it can adversely affect the market performance of the company. Revenue from business activities (LogTR) has been included in the model as a control variable because it reflects the growth of revenue generation from business operations. Finally, the asset turnover ratio (AT) has been included in the analysis as a control variable because it reflects the degree to which a company effectively utilizes its current assets to generate income. A high asset turnover ratio indicates strong operational efficiency and may have a positive impact on market value. In short, we included financial performance measures in different domains (liquidity, profitability, efficiency, and financial leverage) as control variables and included only one measure in each domain to avoid multicollinearity problems.

4. Findings

The two-stage system GMM model estimation results are shown in Table 5 below. AR (1) and AR (2) are the probability values of the first and second order autocorrelation. The Hansen test shows the probabilities of the null hypothesis that asserts the validity of the instrumental variables. Wald test probability values give the significance of the model. The probability value of the Wald- χ^2 statistic (2.66e+06), which shows the significance of the model as a whole, is statistically significant at the 1% level. When the estimation results of the lagged dependent variable LogMCap (-1), which provides information about the validity of the dynamic features in the model, are examined, it is seen that the coefficient is statistically significant and positively correlated with the dependent variable. This result can be considered as a finding that the dynamic model should be preferred.

When the model results are examined, the null hypothesis that there is no AR (1) first-order autocorrelation in the model is rejected. Thus, the null hypothesis that quadratic autocorrelation is not AR (2) is accepted. Since System GMM introduces a large number of “weak” instrumental variables that can lead to biased estimates, the number of instrumental variables should not exceed the number of observations. When the table is examined, the number of instrument variables (10) does not exceed the number of observations (2044). The fact that the probability (prob.=0.445)

value of the Hansen test statistic is greater than 0.05 or 0.10 indicates that the instrumental variables are valid.

Table 5. GMM Model Estimation Results

Dependent Variable: LogMCap		
Variables	Coefficient	Probability
LogMCap ₍₋₁₎	0.718***	0.000
CE	-0.000	0.563
CS	0.000	0.582
CG	0.002**	0.011
ROA	0.80***	0.000
CR	0.010**	0.014
TATE	-0.001***	0.000
LogTR	0.266***	0.000
AT	-0.088***	0.000
Wald- χ^2 (chi2) (probability)	2.66e+06 (0.000)	
Number of groups	393	
AR1(probability)	0.000	
AR2(probability)	0.186	
Sargan (probability)	0,32	
Hansen(probability)	0.445	
Number of instruments	10	
Number of observations	2044	

Note: ***, **, * indicate significance at 1%, 5% and 10% significance level, respectively.

Regarding the core variables of interest, the Governance Controversies score (CG) is positively and significantly associated with market value ($\beta = 0.002$, $p < 0.05$). This suggests that firms with fewer governance controversies, reflected in higher CG scores, are rewarded by investors with higher valuations. This finding aligns with the findings of various studies (e.g., Wu et al., 2023; Brinette et al., 2023. Yet, Environmental (CE) and Social (CS) controversy scores were not found to have a statistically significant effect on market value. Strong governance practices are often linked to better long-term performance. Thus, higher CG scores positively impact stock prices and firm value.

Our findings are in line with the findings of the studies which assert that ESG controversies have a negative impact on firm value implying higher ESG Controversies scores are positively associated with higher ESG Controversies scores. The positive and statistically significant relationship between Governance Controversy Scores and firm value can be attributed to the direct impact of governance on operational performance, investor perceptions, and the unique dynamics of the energy sector. The lack of a similar association for Environmental and Social Controversies may stem from sector-specific characteristics, stakeholder priorities, and the complexity of measuring and reporting these issues. There is a positive and statistically significant relationship between market value and the control variables of ROA, CR, LogTR and LogMCap, while there is a negative and statistically significant relationship between market value and control variables of TATE and AT.

5. Conclusion

Industries with fundamental environmental and social risks, such as energy, oil, gas, mining, and nuclear, face higher exposure to controversies in the public. These industries must

secure and maintain a "social license to operate" (SLO), an unwritten contract with stakeholders that legitimizes their operations (Curran, 2017; Hoffmann and Kristensen, 2017). Although a few recent studies have explored ESG controversies arising from various causes, such as corruption and scandals, this study is one of the first studies that explores the potential impacts of different dimensions of ESG controversies (environmental, social, and governance) on the market value of firms in the energy sector, to the best of our knowledge.

We employ a dataset of 393 firms in the energy sector to propose a new perspective in evaluating the impact of ESG controversies on market value in the Energy sector by using ESG Controversies Scores. The findings of our study reveal that the market value of firms in the previous period has had a statistically significant positive effect on the market value of firms in the current period. Our analysis reveals a positive and statistically significant association between Governance Controversy scores and market value. Our findings suggest governance controversies have the most direct and measurable impact on firm value in the energy sector, possibly due to their stronger influence on operational performance and investor confidence. On the other hand, environmental and social controversies do not exhibit a significant impact. Implications of the study may help investors and policymakers to make decisions that prioritize ESG considerations in the energy sector, as firms with fewer governance controversies are rewarded by investors with higher valuations. In this study, the findings emphasize the importance of stronger corporate governance, which implies that companies should reduce their involvement in governance-related controversies, which are related to executive compensation, insider trading, anti-competition, bribery, and corruption, to strengthen market value. Negative media publicity regarding board members' or executives' actions, and about the function of the board, would have adverse effects on the interests and wealth of the shareholders and ultimately would deteriorate the market value of firms. Therefore, the board of directors should be more involved in the implementation of strong corporate governance mechanisms to avoid such governance-related controversies in the energy sector.

This research is not without limitations. The number of firms examined has been limited to 393 due to data availability constraints. As ESG reporting becomes increasingly standardized and mandatory under various regulations, ESG controversy scores are expected to become more widely available, which will allow future studies to utilize larger and more comprehensive datasets. Also, to better capture delayed market responses, future research may explore the long-term effects of ESG controversies using multi-year lag structures or event-study methods. While this study focuses on the energy sector, it treats the sector as a single homogeneous group. Sectoral comparisons may help to determine whether the asymmetric importance of corporate governance controversies in our study is unique to the energy sector or can be considered in other sectors.

Declaration of Research and Publication Ethics

This study, which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher's Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There is no potential conflict of interest in this study.

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THE IMPACT OF ENVIRONMENTAL TECHNOLOGIES AND ENVIRONMENTAL POLICY STRINGENCY ON ENVIRONMENTAL DEGRADATION

Çevreyle İlgili Teknolojilerin ve Çevresel Politika Katılığının Çevresel Bozulmaya
Etkisi

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Abstract

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Stringency, Dynamic
Panel Data.

JEL Kodları:
O13, Q50, Q55, Q58.

Anahtar Kelimeler:
Çevresel Bozulma,
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JEL Codes:
O13, Q50, Q55, Q58.

The increase in global warming and environmental pollution accelerates ecological degradation and prompts governments worldwide to adopt policies aimed at addressing environmental challenges while maintaining economic growth. In this context, this study examines how environmental technologies and policy stringency affect CO₂ emissions using panel data from 38 OECD countries for the period 1990-2022. The analysis, based on fixed effects and Driscoll-Kraay (1998) estimators, reveals that per capita GDP, exports, industrial activities, fossil fuel consumption, and education expenditures support economic expansion but also contribute to higher emission levels. The results indicate that both energy use and policy stringency significantly impact emission outcomes. While the proportion of environmental technologies reduces emissions, the unexpected positive relationship shown by the number of patents may be attributed to the time lag between the implementation of patents or to the production of more patents in high-emission countries. Overall, the findings indicate that environmental innovation alone cannot achieve emission reductions; it must be supported by strong policy implementation.

Öz

Küresel ısınma ve çevre kirliliğinin artışı ekolojik bozulmayı hızlandırmakta ve dünya genelinde hükümetleri ekonomik büyümeyi korurken çevresel zorlukları ele almayı amaçlayan politikalara yöneltmektedir. Bu bağlamda, 1990-2022 dönemi 38 OECD ülkesine ait panel verileri kullanan bu çalışmada, çevre teknolojilerinin ve politika katılığının CO₂ emisyonlarını nasıl etkilediği araştırılmaktadır. Sabit etkiler ve Driscoll-Kraay (1998) tahmincilerine dayanan analiz, kişi başına düşen GSYİH'nin, ihracatın, endüstriyel faaliyetlerin, fosil yakıt tüketiminin ve eğitim harcamalarının ekonomik genişlemeyi desteklediğini ancak aynı zamanda daha yüksek emisyon seviyelerine de katkıda bulunduğunu ortaya koymaktadır. Çıkan sonuçlara göre hem enerji kullanımı hem de politika katılığı emisyon sonuçlarını önemli ölçüde etkilemektedir. Çevresel teknolojilerin oranı emisyonları azaltırken, patent sayısının gösterdiği beklenmedik pozitif yönlü ilişki, patentlerin ortaya çıkması ve uygulamaya geçmesi arasındaki gecikmeye veya yüksek emisyonlu ülkelerde daha fazla patent üretilmesine bağlanabilir. Genel olarak bulgular, sadece çevresel inovasyonun emisyon azaltımları sağlamak için yeterli olmadığını; güçlü politika uygulamaları ile desteklenmesi gerektiğini göstermektedir.

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1. Introduction

Sustainable development seeks to address the long-term well-being of society by harmonizing objectives of growth with breakthroughs that aim for development without any environmental deterioration (Ahmad et al., 2023). However, population growth, rapid urbanization, and structural transformations create pressures on the environmental system, throwing it out of natural balance. These pressures tend to release harmful pollutants and emissions into the system, and over time, lead to resource and habitat depletion (Yeganeh, 2020). Thus, the degradation of the environment threatens the system as well as human health, quality of life, and development (World Bank, 2016). The document by Tang et al. (2023) states that the predominant driver of climate change and global warming is the rise of CO₂ emissions, which constitute nearly 75% of the world’s greenhouse gas emissions. The IPCC (2018) has even predicted that this could lead to significant environmental and socio-economic challenges in the near future.

Environmental technology or innovation is defined as the integration of scientifically based experts into societal decision-making processes aimed at preventing or reducing ecological degradation (Marx, 1992). These innovative ecosystems are groups of people, organizations, universities, government agencies, and institutions that develop the infrastructure to deliver and disseminate new developments and turn them into concrete practice. (Markard and Truffer, 2008). In addition to the advancement of techniques, eco-innovation also involves the organizational, societal, and cultural behavioral dimensions, and this is a multi-layered process of transformation (Rennings, 2000). In this context, the development and use of environmentally associated technologies and techniques that assist in the lowering of greenhouse gas emissions and ecological footprints are fundamental to the achievement of the objectives of sustainability (Wang et al., 2020a; Suki et al., 2022).

Energy efficiency technology reduces resource consumption in manufacturing processes (Samargandi, 2017). Patents in carbon-free energy domains demonstrate the potential for innovation (Wang et al., 2012). Peng et al. (2022) suggest that integrating technologically advanced knowledge, skills, and infrastructure leads to a multi-layered economic framework, enabling creative solutions. Information and communication technologies (ICTs) can be effective in reducing emissions through increasing productivity and industrial optimization purposes (Adebayo et al., 2022), and technology-focused indicators such as fixed-line and mobile phone usage are observed to be used in measuring their impact on CO₂ emissions (Su et al., 2021). Similarly, it applies to renewable electricity generation through wind, solar, and other biomass components, which reduce carbon emissions by reducing the use of fossil fuels (Bhatia, 2014; Bilgili et al., 2025). The field of environmental technologies also encompasses bioremediation, in which microorganisms are used to reduce pollutants (Das et al., 2023), artificial intelligence-based water management (WIPO, 2024), waste management, and eco-design (Sharma et al., 2024). In addition, the development of the digital economy, clean energy infrastructure, and energy-saving technologies promotes the spread of eco-innovations (Zhao et al., 2024); meanwhile, financial innovations and the quality of institutions also help reduce environmental degradation (Hussain and Dogan, 2021; Huo et al., 2023).

Policy created at the same time as technological advances helps to mitigate degradation. Modern policies try to integrate environmental damage into the cost of Pigou (1920) conceptualized environmental damage as a negative externality. As emphasized in Ajeigbe and

Ganda (2024), Many countries have imposed stricter environmental regulations in an effort to control degradation and to attain sustainability. As supported by Neves et al. (2020) and the OECD (2016), the reason for implementing strict environmental policies is to encourage both producers and consumers to make environmentally friendly choices by changing their behavior. These policies make environmentally harmful practices less attractive. In particular, the content and strictness of environmental policies implemented by governments have become an important factor in determining the direction of environmental degradation. The Environmental Policy Stringency (EPS) index was built for OECD member states, which allows them to measure and compare efforts made by different countries regarding the strictness of their environmental policies and the resulting necessary policy instruments in the area. Policy instruments were evaluated in the index as explained in the theoretical basis and methods of calculation by Botta and Kořluk (2014). In the first iteration, the index simply evaluated market-based policy instruments, which included carbon taxes, energy taxes, emissions trading systems, and market instruments like research and development (R&D) subsidies, feed-in tariffs, and renewable energy auctions. Subsequently, non-market instruments were included in the evaluation system, which included mandatory and voluntary standards and support and mixed technology instruments (Kruse et al., 2022). Each of the instruments is scored based on the stringency and is amalgamated in a composite measure, which serves the purpose of assessing and comparing countries and cross-temporal comparisons (Frohm et al., 2023).

The EPS index provides a comprehensive data structure and, in this capacity, allows for the empirical testing of theoretical approaches used to examine the relationship between economic growth, policy stringency, and environmental innovation, as well as those employed to explain environmental degradation. In the hypothesis proposed by Kuznets (2019) and subsequently developed, it is stated that environmental degradation will increase in the initial stages of economic growth and will decrease in later stages with the development of environmentally focused policies and technologies. In addition, Porter and van der Linde (1995) argued that well-designed environmental policies could facilitate the adoption of environmentally focused technologies and thereby help reduce environmental degradation. Within the framework of these hypotheses, two important variables emerge that serve to reduce environmental degradation, and these are: environmental technologies and policy stringency. While the reduction of emissions and resource consumption largely relies on innovative technologies, additionally, policy stringency plays a role in creating the necessary market, economic, and regulatory conditions for the adoption and dissemination of these technologies. Therefore, addressing it by including environmental innovation and the stringency of environmental policies is of great importance in balancing strategic frameworks in the pursuit of sustainable development.

In the literature, it is observed that the effects of environmental technologies and environmental policy stringency on environmental degradation are mostly not examined together. In only one study conducted by Güler and Doęan (2023), the interaction between policy and innovation was examined together, designed with a limited sample size and time frame. As a result, it has been determined that the joint consideration of environmental technologies and policy participation, as well as their impacts on environmental degradation, has not been sufficiently researched over a broader scope and longer time span that includes OECD countries. This research aims to address these gaps and contribute to the literature. In the study where tests were conducted using the panel data method with annual data from 38 OECD countries covering

the years 1990-2022, analyses including fixed effects and Driscoll-Kraay (1998) estimators were performed, and a comprehensive assessment of long-term trends was presented.

Furthermore, this study looks into the combined effect of environmental technologies and policy strictness on carbon emissions and establishes a framework for the collaborative influence of regulatory factors on environmental outcomes.

2. Literature Review

The literature has two basic assumptions about the relation between technological development, economic growth, and degradation of the environment. The two hypotheses are the Environmental Kuznets Curve (EKC) and the Porter and van der Linde Hypothesis. The EKC, initially proposed by Kuznets (2019) to focus on income inequality and subsequently modified by Grossman and Krueger (1991), implies an inverted U-shaped relationship between economic growth and pollution. According to the EKC theory, environmental degradation increases during the early stages of economic growth before decreasing once a certain income level is achieved. This theory forms the base of Several studies exploring the relation between growth and damage to the environment. However, Porter and van der Linde (1995) argue that while regulations related to the environment may raise manufacturing costs at first, they may also encourage creativity and improve competitiveness in the long run. Porter and van der Linde claim that effective regulation of the environment could motivate businesses to create cleaner and more efficient technologies, enabling concurrent advances in economic and environmental performance.

According to several studies in the literature, environmental innovation and technology play an essential role in reducing environmental harm. Jebli et al. (2020) claim that switching to renewable energy sources and enacting energy efficiency laws are essential strategies in the fight against climate change. As stated by Jin et al. (2022), China’s policies promoting environmental innovation and human capital development have been effective in reducing carbon emissions in both the short and long term. Suki et al. (2022) state that the use of renewable energy and environmental innovation can significantly reduce carbon emissions and ecological footprints. Liu et al. (2022) draw attention to the geographical component of these processes, demonstrating that environmental innovation has a beneficial knock-on impact in nearby provinces in addition to lowering carbon intensity within areas. Similarly, Bilgili et al. (2025) state that increasing the use of renewable power and environmental technology may significantly reduce CO₂ emissions in Europe.

The importance of technological innovation is also emphasized through analyses across various countries. Wang et al. (2012) emphasized the importance of innovation in achieving a low-carbon economy, highlighting that patents in carbon-free energy technologies significantly reduce emissions. Samargandi (2017) emphasizes that GDP growth increases emissions in Saudi Arabia both in the short and long term, agricultural value added reduces emissions, and technological innovation shows limited efficiency gains. Similarly, Ganda (2019) states that although the use of renewable energy and R&D expenditures generally reduce emissions in OECD countries, certain forms of technological development may temporarily increase emissions, and the environmental impact of technology depends on the structure and maturity of the economy.

Recent research has enriched the literature by providing information concerning policy on renewable energy, economic complexity, and digitalization. Wang et al. (2020a) accentuate the promotion of green technologies and renewable energy to be used as strategies to contain

emissions with almost equal rates of economic growth. Akyol and Mete (2021) confirm that even in OECD countries where energy use and economic growth are still the major causes of environmental degradation, emission reduction is significantly achieved through technology innovation. Su et al. (2021), in a study analyzing BRICS countries, found that while broadband and fixed-line internet led to high levels of emissions, the adoption of mobile technology reduces emissions. Adebayo et al. (2022) prove that information technology development in advanced economies like Denmark, Japan, and Sweden causes an increasing degree of energy efficiency and a decreasing level of emissions because of optimization effects. Similarly, Peng et al. (2022) point out that when countries' economic complexity goes beyond a certain value, emissions will reduce given advancement in technological capabilities as well as production efficiency. Albaker et al. (2023), using the quantile regression method on the MENA region, reveal that the use of renewable energy consistently decreases emissions at all income levels; however, green innovation and energy efficiency may, at the beginning, lead to an increase in emissions within low-quantile economies only. In alignment with this study, Zhao et al. (2024) posit that the digital economy bolsters the emission-reducing role played by green innovation; thus, showing how digital transformation strengthens environmental technology's effectiveness towards sustainability achievement.

Similar to the literature on technological innovation, awareness about the impact of EPS on environmental degradation is increasing. Ouyang et al. (2019) proved that EPS, in the case of OECD countries, contributes positively to environmental quality when regulatory thresholds are crossed and implies non-linear effects. According to De Angelis et al. (2019), stringent environmental regulations tend to favor innovation and sustainable growth in the long run after an initial cost disadvantage. This perspective reflects the Porter Hypothesis. Similarly, Wang et al. (2020b) demonstrate that stricter environmental policies capture more pollution and thus improve air quality, confirming the cost-channel mechanism of the hypothesis. Wolde-Rufael and Mulat-Weldemeskel (2020, 2021) show evidence in developing countries that expansion of EPS used in policy frameworks increases the proportion of renewable energy and decreases CO₂ emissions, albeit with an impact of differing magnitude depending on developmental stage. Wang et al. (2022) counters this by explaining the ineffectiveness of EPS through EPS's economic structure and technological capacity in developing economies. This suggests that the results of policies are influenced by the level of industrial sophistication in the country. Albulescu et al. (2022) introduce the temporal dimension by demonstrating asymmetrical effects whereby emissions are reduced with the tightening of policies, but an increase in the relaxation of policies has long-lasting negative impacts on the quality of the environment. Assamoi and Wang (2023) show that while EPS does enhance environmental performance, greater macroeconomic uncertainty can dampen that association, suggesting that certain stability conditions have a moderating impact. Frohm et al. (2023) further support this by demonstrating that EPS-related emission reductions are significantly higher in high-emission sectors, such as the energy and heavy industry, suggesting there is greater sectoral heterogeneity in the outcomes of policies. Last, Güler and Doğan (2023) indicate that innovation serves as a synergistic complement to EPS and that in combination, the two greatly improve emission reductions beyond what is possible by either alone.

The literature delineates patterns of complex interactions involving economic development, environmental technologies, and the stringency of enacted policies. The Porter Hypothesis emphasizes that strict environmental policies can promote environmental improvement by supporting

innovation, while the Kuznets curve highlights that environmental degradation will increase in the early stages of development but will decrease once a certain income threshold is reached.

Overall, advancing environmental technologies, such as green innovation, digital development, and the use of renewable energy, help reduce emissions, while the importance of this effect depends on factors such as firm strength and economic complexity. As Porter pointed out, tough environmental rules encourage invention and decrease pollution, which helps innovation progress and supports sustainability. The form of environmental rules, economic balance, and varied levels of implementation among nations and industries can all influence how significant this impact is. To completely explain these disparities, institutional channels corresponding to aspects such as governance quality, institutional capability, and implementation variances must also be considered. In this context, the assessment of the literature covers findings from studies covering several nations and scopes, as well as studies on environmental technology and environmental policy stringency, which are consistent with the research's objective.

In conclusion, these findings highlight that the achievement of sustainable outcomes in the environment is dependent, in equal measure, on technological progress and policy architecture, and on the institutional structures that govern their interplays and execution. However, the body of research investigating the synergy of the impacts of environmental technologies alongside the impacts of the stringency of environmental policies on environmental degradation remains thin. Therefore, this research attempts to fill this void by pursuing a multidimensional framework that combines both the technological and policy dimensions to capture how innovation and policy stringency, in tandem, determine outcomes on the environment.

3. Methodology

This research is trying to assess the consequences of environmental technologies and the strength of environmental policy covering the years 1990 to 2022 for OECD countries. Since the analysis involves multiple countries over time, panel data is a suitable analysis for this study. Panel data, often referred to as data of a longitudinal nature, merges cross-sectional views with time-series trends by following multiple units (such as individuals, organizations, or nations) over time. This format allows researchers to observe differences between units and identify dynamic patterns that single cross-sectional or time-series datasets may miss. Panel data models offer several advantages, such as (Baltagi, 2005: 4-5); (i) Accounting for time-invariant unobserved heterogeneity, (ii) Panel data could utilize lagged variables to reflect dynamic behavior, (iii) The combination of information across two dimensions enhances efficiency and increases degrees of freedom.

In general, panel data analysis can be estimated through Fixed-effects (FE) and Random-effects (RE) estimators. The fixed-effects model controls for time-invariant unobserved heterogeneity by estimating unit-specific intercepts. This is suitable when the unobserved heterogeneity is linked to the explanatory factors. The assumption is that α_i may be associated with x_{it} , which means that ordinary least squares (OLS) estimates may be biased if this correlation is not properly addressed. The standard fixed effect model may be written as follows (Wooldridge, 2010: 9-10):

$$y_{it} = \alpha_i + \beta x_{it} + \epsilon_{it} \quad (1)$$

where; y_{it} is the dependent variable for unit i at time t , α_i is the unit-specific intercept, x_{it} are the explanatory variables, ϵ_{it} is the error term.

On the other hand, the Random Effects Model (RE), assumes that the specific effect for each individual α_i is not related to the explanatory variables and treats it as a random draw, leading to more efficient estimates under exogeneity. The RE model is expressed as (Greene, 2012: 411):

$$y_{it} = \alpha + \beta x_{it} + \mu_{it} \quad (2)$$

$$\mu_{it} = \mu_i + \epsilon_{it} \quad (3)$$

The idiosyncratic error referred to as ϵ_{it} , whereas μ_i represents the random individual-specific component. RE outperforms FE if there is no association between μ_i and x_{it} . Otherwise, it produces biased results. There are two ways to estimate panel data (FE and RE), so to decide which way is more appropriate Hausman test is commonly used.

The Hausman test could be used to determine whether FE or RE is ideal for the estimated model. In addition, the Hausman test helps to inform whether the unit-specific effects are associated with the error term. If the unit-specific effects are not significantly associated with the error term, the random effects model is more relevant; however, the fixed effects model is the optimal way. The test equation below (Hausman, 1978):

$$H = (\beta^{RE} - \beta^{FE})' [Var(\beta^{RE}) - Var(\beta^{FE})]^{-1} (\beta^{RE} - \beta^{FE}) \quad (4)$$

A significant test statistic implies rejecting the null hypothesis in favor of the fixed effects model, indicating that the no-correlation assumption is violated.

Driscoll–Kraay (1998) standard errors are a robust covariance matrix estimator designed for linear panel data models. They extend heteroskedasticity and autocorrelation consistent estimators, such as Newey–West, to the panel data setting. A key advantage is that they provide consistent inference even when the error structure exhibits heteroskedasticity, serial correlation, and cross-sectional dependence. This makes them particularly suitable for macroeconomic panels with a relatively small number of cross-sections but a sufficiently large time dimension T . The regression model can be written as (Driscoll and Kraay, 1998):

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it}, i = 1 \dots, N; t = 1 \dots, T \quad (5)$$

where; y_{it} is the dependent variable, α_i is the unit-specific fixed effects, x_{it} represents the explanatory variables, μ_{it} is the error term.

Driscoll–Kraay robust standard errors are widely used because they address several violations of the classical regression assumptions simultaneously. They remain valid in the presence of heteroskedasticity, where the variance of the error term differs across time or units; they also correct for autocorrelation, allowing for serial correlation of errors within panels, whether first-order or higher-order; and, unlike cluster-robust estimators, they explicitly account for cross-sectional dependence, capturing contemporaneous correlations of errors across units at the same point in time (Hoechle, 2007; Vogelsang, 2012).

4. Data & Model

This study used a combination of annual data of economic, environmental, and innovation-related variables, primarily sourced from the World Bank (2025) and the OECD (2025). Each variable is briefly explained below (Table 1).

Table 1. Data Explanation & Source

Variables Explanation	Variable	Source
Logarithm of GDP per capita	Ln-PERCAP	World Bank
Exports calculated as a proportion of GDP	EXP	
Manufacturing’s contribution to GDP (%)	MFAC	
Fossil fuel energy consumption (% of total)	FFCON	
Electricity production from renewable sources, excluding hydroelectric (% of total)	EPFRS	
Government expenditure on education (% of GDP)	EXPOEDU	OECD
Environmental degradation	CO2	
Percentage of environmental patents	POINVT	
Patents on environmental technologies	POENVT	
Environmental Policy Stringency Index	EPS	

This study uses annual data between 1990–2022 for 38 OECD countries to investigate how environmental-related technologies and the strength of policy have an impact on carbon emissions. Panel data analysis was used to perform the empirical investigation. The analysis started with a correlation test to explore relationships among the dependent variables. The Hausman test was then applied to determine whether the fixed-effects or random-effects model was more suitable. The Wald test and the Wooldridge test were then used to check for heteroskedasticity and first-order autocorrelation, respectively. The results indicated the presence of both issues. In addition, formal tests for cross-sectional dependence could not be carried out because the data set was severely unbalanced. To account for possible dependencies within units, Driscoll–Kraay robust standard errors were employed, which are robust to both heteroskedasticity and autocorrelation as well as to cross-sectional correlation (Driscoll and Kraay, 1998; Hoechle, 2007):

$$CO_2 = \alpha_i + \beta \text{ Control Variables} + \beta \text{ Explanatory Variables} + \mu_{it} \quad (6)$$

where the control variables include Ln-PERCAP, EXP, MFAC, FFCON, EPFRS, and EXPOEDU; and the explanatory variables are: POINVT, POENVT, and EPS. A detailed explanation of each variable is provided below:

CO₂: This is the dependent variable and represents annual carbon dioxide emissions (in metric tons per capita) in each country obtained by dividing total national CO₂ emissions by the total population. It is an indirect measure of environmental degradation and is employed in the analysis as the primary independent variable.

Ln-PERCAP: It is the natural logarithm of GDP per capita (constant 2015 US dollars). The natural log is used to normalize the distribution of data, reduce skewness, and improve the measurement of proportional differences in income levels between countries.

EXP: This indicator represents the weight of exports in an economy. It is calculated by the total exports of goods and services as a percentage of gross domestic product GDP.

MFAC: It indicates the manufacturing value added percentage in a country's gross domestic product. It is worked out as the proportion of manufacturing value added to GDP, expressed as a percentage.

FFCON: This is a measure of the proportion of total energy use in which consumption comes from fossil fuels such as coal, oil, and gas. It is a measure of the proportion of energy that comes from fossil fuels within total energy usage.

EPFRS: This indicator demonstrates the share of electricity produced from renewable energy sources, excluding hydro. As a percentage of total electric production, not including hydropower, solar energy, wind power, and other non-hydroelectric renewables, contributes to that amount.

EXPOEDU: This indicator reflects the percentage of government expenditure on education as a ratio of GDP. This represents the level of public investment in education. It is included to explore possible indirect effects on environmental awareness and innovation capacity.

POINVT: Based on OECD data, this variable has been calculated by the percentage of green or environment-related patents relative to the total patenting activity in a country.

POENVNT: This variable, obtained from the OECD, measures the number of patents specifically related to environmental technologies. It presents green technological advancement in each country and plays as a key indicator of environmentally associated technological steps

EPS: This index demonstrates the toughness of environmental-related regulations in each country. The higher the index value, the tougher the environmental policies.

Before proceeding with the analysis, it is helpful to provide a summary of each variable. Table 2 presents the descriptive statistics for the data.

Table 2. Summary Statistics of the Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
CO2	1212	8.771512	4.554696	1.13935	32.12177
Ln-PERCAP	1197	10.01643	0.855239	7.296311	11.80344
EXP	1235	44.30218	28.4783	8.81647	213.2227
MFAC	1128	15.42277	4.897782	3.912374	37.14683
FFCON	1254	74.37317	17.71773	10.25	100
EPFRS	1147	7.505317	12.42334	-69.5753	81.55761
EXPOEDU	1039	5.131914	1.16128	1.93433	8.58383
POINVT	1212	2.452989	6.00653	.000902	33.92035
POENVNT	1136	10.38864	4.79643	0.9	50
EPS	1178	1.881909	1.177785	0	4.888889

Before proceeding with the analysis, demonstrating the graph between the dependent variable and explanatory variables will clarify the relationship between the dependent and explanatory variables. The graphics are like below (Figure 1).

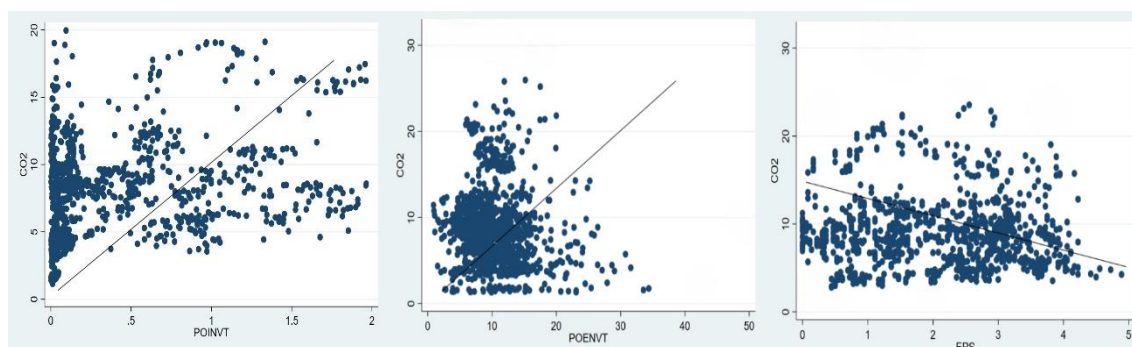


Figure 1. Time Series Plots of the Relationship Between CO2 and Environmental Technology, Environmental Policy Stringency Variables

Overall, Figure 1 suggests that while patents on environmental technologies (POENVT) and the percentage of environmental patents (POINVT) may contribute to higher emissions, the Environmental Policy Stringency Index (EPS) could be associated with emission reductions. These preliminary visual insights will be further examined in the statistical analysis.

Before proceeding with the analysis, a correlation test was conducted to check for potential multicollinearity. Table 3 presents the results of this test.

Table 3. The Results of Correlation Test

		1	2	3	4	5	6	7	8	9	10
1	CO2	1									
2	Ln-PERCAP	0.43	1								
3	EXP	0.21	0.30	1							
4	MFAC	-0.15	-0.30	-0.00	1						
5	FFCON	0.30	-0.20	-0.02	0.12	1					
6	EPFRS	-0.29	0.24	0.08	-0.17	-0.28	1				
7	EXPOEDU	0.08	0.35	-0.05	-0.35	-0.45	0.25	1			
8	POINVT	0.29	0.21	-0.30	0.20	0.14	-0.09	-0.15	1		
9	POENVT	-0.10	-0.03	0.07	-0.17	-0.03	0.21	0.02	0.99	1	
10	EPS	0.04	0.58	0.31	-0.15	-0.09	0.34	0.10	0.25	0.23	1

According to the results of the correlation test, only one relatively high correlation was observed (between POINVT and POENVT). However, since these variables will be included in the model separately, this will not be considered a problem. The VIF test was performed to detect the absence of multicollinearity. VIF values of 5-10 may be a sign of moderate multicollinearity, while VIF exceeding 10 points to severe multicollinearity (Wooldridge, 2013: 98). As shown in the Table 4, all VIF values are far from exceeding these benchmarks; therefore, multicollinearity is not an issue for the estimated model.

Table 4. The Results of VIF Test

Variable	VIF	1/VIF	Variable	VIF	1/VIF
Ln-PERCAP	1.89	0.52785	Ln-PERCAP	2.13	0.469152
EPS	1.8	0.554889	EXPOEDU	1.69	0.590914
EXPOEDU	1.62	0.617715	EPS	1.61	0.620966
FFCON	1.33	0.752019	POINVT	1.58	0.630972
EPFRS	1.28	0.77984	EXP	1.48	0.675047
POENVNT	1.28	0.78138	FFCON	1.34	0.743939
MFAC	1.28	0.78415	MFAC	1.33	0.751668
EXP	1.13	0.881412	EPFRS	1.24	0.80911
Mean/VIF	1.45		Mean/VIF	1.55	

Before proceeding to the estimation, the Hausman test needs to be estimated to decide if a fixed or random effects model is more suitable. The Hausman test results indicate that the fixed effects estimator is more suitable for the model used in this study. Given these findings, the results of the fixed effects estimation are presented Table 5.

Table 5. The Estimation Results of Fixed Effect

Variables	(1) CO2	(2) CO2	(3) CO2	(4) CO2	(5) CO2	(6) CO2
Ln-PERCAP	1.359*** (0.114)	1.202*** (0.110)	1.349*** (0.116)	1.747*** (0.141)	1.525*** (0.138)	1.748*** (0.141)
EXP	-0.0297*** (0.00470)	-0.0267*** (0.00450)	-0.0286*** (0.00481)	-0.0239*** (0.00484)	-0.0212*** (0.00466)	-0.0240*** (0.00484)
MFAC	0.205*** (0.0192)	0.173*** (0.0187)	0.205*** (0.0200)	0.175*** (0.0204)	0.149*** (0.0199)	0.177*** (0.0205)
FFCON	0.117*** (0.00829)	0.129*** (0.00802)	0.116*** (0.00848)	0.107*** (0.00848)	0.120*** (0.00830)	0.108*** (0.00851)
EPFRS	-0.0458*** (0.00491)	-0.0375*** (0.00477)	-0.0441*** (0.00504)	-0.0425*** (0.00498)	-0.0358*** (0.00486)	-0.0426*** (0.00498)
EXPOEDU	0.186*** (0.0593)	0.133** (0.0569)	0.176*** (0.0597)	0.204*** (0.0590)	0.151*** (0.0571)	0.201*** (0.0591)
POINVT		0.217*** (0.0231)			0.209*** (0.0247)	
POENVNT			0.00146 (0.00899)			0.00908 (0.00900)
EPS				-0.340*** (0.0705)	-0.281*** (0.0681)	-0.353*** (0.0716)
Constant	-15.90*** (1.447)	-15.20*** (1.383)	-15.73*** (1.471)	-18.29*** (1.545)	-17.17*** (1.491)	-18.43*** (1.551)
Observations	941	941	904	904	904	904
R-squared	0.573	0.611	0.550	0.562	0.596	0.562
Number of Groups	38	38	38	38	38	38

Note: Standard errors in parentheses-*** p<0.01, ** p<0.05, * p<0.1

While the first model presents results only for the control variables, Models 2, 3, and 4 show the effects of the explanatory variables individually. Models 5 and 6 include the explanatory variables together. Since POINVT and POENVNT are highly correlated, they were included in the model separately. Ln-PERCAP, MFAC, FFCON, EXPOEDU, and POINVT (Per capita income, manufacturing, fossil fuel energy consumption, Government expenditure on education, Percentage of environmental patents), all show positive and statistically significant effects on CO₂

emissions, which shows that economic growth and industrial activities, including fossil fuel energy consumption and manufacturing, contribute to environmental degradation. Electricity production from renewable sources (Green Energy Adoption) and exports has a negative and significant effect, confirming its role in reducing emissions. Environmental policy stringency also shows a negative and significant impact, suggesting that stronger regulations are effective. In contrast, the percentage of environmental technologies and patents on environmental technologies has statistically insignificant effects. Wald test indicates the presence of heteroskedasticity ($\chi^2(38) = 2111.80$, $p = 0.0000$) and Wooldridge test indicates the presence of first-order autocorrelation ($F(1,37) = 637.944$, $p = 0.0000$), in addition Durbin–Wu–Hausman test insured the absence of endogeneity Durbin (score) $\chi^2(2) = 2.55151$ ($p = 0.2792$); Wu-Hausman $F(2,918) = 1.26412$ ($p = 0.2830$). So, to address heteroskedasticity and first-order autocorrelation issues, the study applies Driscoll–Kraay estimation, which accounts for both problems effectively.

Table 6. The Estimation Results of Driscoll–Kraay

Variables	(1) CO2	(2) CO2	(3) CO2	(4) CO2	(5) CO2	(6) CO2
Ln-PERCAP	2.424*** (0.192)	1.700*** (0.126)	2.424*** (0.194)	3.077*** (0.192)	2.356*** (0.140)	3.150*** (0.166)
EXP	0.0214*** (0.00393)	0.0386*** (0.00511)	0.0223*** (0.00420)	0.0267*** (0.00467)	0.0465*** (0.00552)	0.0267*** (0.00456)
MFAC	-0.0825*** (0.0120)	-0.141*** (0.0170)	-0.0859*** (0.0127)	-0.0777*** (0.0117)	-0.143*** (0.0129)	-0.0699*** (0.0120)
FFCON	0.0932*** (0.00571)	0.0869*** (0.00629)	0.0933*** (0.00553)	0.0943*** (0.00586)	0.0875*** (0.00628)	0.0939*** (0.00629)
EPFRS	-0.113*** (0.00996)	-0.108*** (0.00977)	-0.110*** (0.00875)	-0.0946*** (0.00640)	-0.0876*** (0.00576)	-0.0979*** (0.00612)
EXPOEDU	0.532*** (0.101)	0.748*** (0.0905)	0.524*** (0.0923)	0.430*** (0.110)	0.654*** (0.0992)	0.430*** (0.121)
POINVT		0.190*** (0.0181)			0.208*** (0.0146)	
POENV			-0.0270 (0.0280)			0.0442 (0.0268)
EPS				-0.898*** (0.0882)	-1.009*** (0.0891)	-0.968*** (0.0716)
Constant	-24.16*** (1.871)	-17.87*** (1.449)	-23.83*** (1.787)	-28.80*** (1.928)	-22.38*** (1.627)	-29.90*** (1.524)
Observations	941	941	904	904	904	904
R-squared	0.458	0.503	0.458	0.492	0.546	0.494
Number of Groups	38	38	38	38	38	38

Note: Standard errors in parentheses-*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 shows the result of the Driscoll-Kraay with carbon dioxide emissions per capita CO₂ as the dependent variable. GDP per capita (Ln-PERCAP), exports (EXP), manufacturing activity (MFAC), and fossil fuel consumption (FFCON) all show positive, significant effects, indicating economic activity drives emissions. In comparison, electricity produced from renewable resources (EPFRS) has a consistent negative effect, suggesting a mitigating role in CO₂ emissions. Government expenditure on Education (EXPOEDU) affects emissions in a positive way, probably as a result of energy consumption in line with energy market development. The percentage of environmental-associated patents (POINVT) has a positive impact on CO₂, which possibly emphasizes initial stage costs, while the number of environmental-associated patents

(POENVT) demonstrates statistically insignificant impacts. The percentage of environmental patents (POINVT) unexpectedly shows a positive and significant effect, indicating that higher patent activity is linked with increased emissions. These unexpected results may mirror a time gap between new innovations and being adopted by the world (this means that the patents may be registered, but not yet adopted). Likewise, countries that have higher emissions may be registering more patents as an effective factor, not as a reflection of the new environmental innovations. Lastly, implementing the environmental-related rules and regulations slowly can lead to low levels of adoption, although a high level of innovation. However, the finding indeed considers that patents are not enough to widespread the technology, and environmental management is required to control the emissions. On the other hand, environmental policy strength (EPS) shows a strong, statistically significant, and negative effect, considering that strict policies play a game-changing role. This means that carbon dioxide emission control policies in OECD countries have been somewhat successful.

5. Conclusion

The present study has investigated the effect of environmental technologies and environmental policy stringency on carbon dioxide emissions across 38 OECD countries for the period 1990–2022 by utilizing a panel data technique. Both fixed effects and Driscoll–Kraay estimations were used to predict the relationship, also Wald and Wooldridge tests were conducted in order to identify respectively heteroskedasticity and first-order autocorrelation. The results consistently indicate that CO₂ emissions are positively associated with GDP per capita, exports, production of manufactures, consumption of fossil fuels, education expenditure, and percentage of environmental patents. On the other hand, renewable penetration and stringent environmental policies are helpful in reducing emissions.

The positive relationship between per capita GDP and emissions is consistent with the Kuznets (2019) hypothesis, which suggests that environmental degradation may increase in the early and middle stages of development as economies industrialize. On the other hand, the observed decrease in emissions with the implementation of stricter policies and the increase in renewable energy usage indicates a Kuznets curve-type turning point. In this context, the negative impact of economic growth on carbon emissions can be eliminated by appropriate policy and technology applications, covering elements such as income increase, structural reforms, and efficiency increase.

The results of the research show that in order for corporate performance and competitiveness to increase, innovation must be taken into the market efficiently. The positive relationship between environmental technologies and environmental degradation shows that just innovation itself does not lower environmental degradation. In this framework, Porter (1995) emphasizes the use of these technologies and the need for policies and corporate applications that increase the industrial applicability. The findings of this study cover Porter (1995) with this emphasis.

The conclusions drawn from this study are consistent with studies in the literature about the relationship between environmental degradation and economic growth and industrial activity (Jianu et al., 2022; Sikder et al., 2022; Cuerdo Mir and Luis Montes Botella, 2024; Dharmapriya et al., 2025). Specifically, GDP per capita, manufacturing activities, fossil fuel consumption, and

education expenditures appear to have a positive impact on the CO₂ emissions. On the other hand, renewable energy use and environmental policy stringency significantly contribute to emission reduction. The result of this research emphasizes previous results of the literature regarding the critical role played by strict policy regulations and technological progress in achieving sustainable development aims (De Angelis et al., 2019; Albulescu et al., 2022; Güler and Doğan, 2023; Assamoi and Wang, 2023; Frohm et al., 2023). For this reason, new environmental-associated technological innovations alone are not enough to keep carbon dioxide under control. This suggests that policymakers should convert their interest from innovation promotion to creating conditions that could lead to the effective application of these innovations. Good environmental policies are essential for the widespread implementation of these innovations and the continued transition to renewable and green energy sources.

Corporate quality, governance capacity, and regulatory effectiveness are factors that could play a considerable role in the success of the policies that focus on environmental issues. Only with these factors will countries be able to have a wide implementation of environmental innovations in industry. Institutions that work in high quality are those that lead to more effective policies and regulations and help achieve a high level of integration of environmental innovation in the industry. Unlike these weak institutions impede this process. Therefore, further research should focus on examining the impact of environmental policies on environmental degradation by including institutional factors like governance indicators.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest

There are no potential conflicts of interest in this study.

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DOES CLIMATE RISK AFFECT CORPORATE FINANCIAL PERFORMANCE? EVIDENCE FROM TÜRKİYE

İklim Riski Kurumsal Finansal Performansı Etkiliyor mu? Türkiye’den Kanıtlar

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Abstract

Climate risk affects not only living things and nature but also, increasingly, firms. Therefore, quantifying the impacts of climate risk on firms and analyzing their impact on financial performance constitutes an important area of research. In this context, the objective of this study is to investigate the effects of climate risk on corporate financial performance. The research applies climate risk indices developed by Bua et al. (2024) as a proxy for climate change risk. For the purpose of this study, firm data for the BIST Sustainability 25 Index, listed non-financial companies, consisting of a panel data set between 2005 and 2023, is applied. In pursuit of this goal, the System Generalized Method of Moments (System GMM) was used, as it is considered a suitable estimator of dynamic panel data in measuring climate hazard impacts on financial performance. The results of the study show that both physical risk and transition risk have negative effects on corporate financial performance. This study provides important insights for policymakers and enterprises in terms of climate risk and corporate financial performance.

Keywords:

Financial
Performance,
Climate Risk,
Sustainability.

JEL Codes:

G32, Q54, Q56.

Öz

İklim riski sadece canlıları ve doğayı değil aynı zamanda giderek artan oranda işletmeleri de etkilemektedir. Dolayısıyla iklim riskinin işletmeler üzerindeki etkilerinin nicelleştirilmesi ve finansal performansları üzerindeki etkilerinin analiz edilmesi önemli bir araştırma sahası oluşturmaktadır. Bu bağlamda, bu çalışmanın amacı, iklim riskinin kurumsal finansal performans üzerindeki etkilerini araştırmaktır. Çalışmada iklim değişikliği risk ölçüsü olarak Bua vd. (2024) tarafından geliştirilmiş iklim risk endeksleri kullanılmaktadır. Araştırma kapsamında firma verileri olarak ise BIST Sürdürülebilirlik 25 Endeksi’nde yer alan finansal olmayan firmalara ait 2005–2023 dönemini kapsayan panel veri seti kullanılmaktadır. Bu doğrultuda, iklim risklerinin firma performansı üzerindeki etkilerini değerlendirebilmek amacıyla dinamik panel veri analiz tekniklerinden biri olan Sistem Genelleştirilmiş Momentler Yöntemi (System GMM) uygulanmıştır. Çalışma sonuçları hem fiziksel riskin hem de geçiş riskinin kurumsal finansal performans üzerinde olumsuz etkileri olduğunu göstermektedir. Bu çalışma iklim riski ve kurumsal finansal performans açısından politika yapıcılar ve işletmeler için önemli çıkarımlar sunmaktadır.

Anahtar Kelimeler:

Finansal Performans,
İklim Riski,
Sürdürülebilirlik.

JEL Kodları:

G32, Q54, Q56.

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1. Introduction

NASA (National Aeronautics and Space Administration) states that climate change is a gradual shift in the mean patterns of weather that characterize the local, regional, and global climates of the Earth. Two key conclusions can be drawn from this definition. First, climate change occurs as a consequence of prolonged environmental degradation. Second, the impacts of climate change usually extend over a large region. When examining the potential impacts of climate change over the next five years, it is projected that precipitation patterns will show significant regional variations, Arctic warming will continue to exceed the global average, and temperatures will continue to rise (WMO, 2025). All these imminent climate threats are affecting living beings, companies, institutions, and governments, forcing them to prepare action plans.

Bua et al. (2024) classify risks arising from climate change as physical and transition risks. Physical climate risks arise from the tangible effects of climate change. These include climate events such as floods, forest fires, extreme heat, drought, and coastal flooding. Transition risks, on the other hand, arise from the uncertainty surrounding the transition to a more sustainable, net-zero emissions economy.

According to the Intergovernmental Panel on Climate Change's (IPCC, 2022) climate change report, physical climate risks lead directly to production losses, particularly in sectors such as agriculture, fisheries, and tourism. They also inflict damage on ports and assets of energy companies; heat induces significant labor productivity losses. The International Energy Agency (IEA) net-zero emissions report highlighted that transition risks can trigger immediate carbon price shocks, oil and automobile sector demand shifts, and asset stranding in the form of fossil fuel reserves, coal and pipelines, and thermal power plants.

It is widely accepted that both physical and transition risks possess the potential to significantly affect global macroeconomic and financial channels. A study by the International Monetary Fund (IMF) released in 2023, which is captioned 'Global Economic Impacts of Physical Climate Risks,' supports the framework and also emphasizes that climate risks can contribute to disruption in supply chains, an increase in costs, and the reorientation of global trade flows. The channels indicate that the latter impacts growth and inflation on the macroeconomic front. The Network for Greening the Financial System's (NGFS, 2020) report of 2020 also indicates that climate risks beget systemic risks in the context of bank lending, insurance activities, and investment management. The report also notes the adverse developments associated with these threats, for instance, increased insurance expenditures and having larger fiscal impacts on the finances of the public.

Scanning the IMF paper (Global Economic Impacts of Physical Climate Risks- Lepore and Fernando, 2023), indicates that the effects of climate risk are meaningfully different in nations and industries. For instance, the report highlights that countries with middle incomes, and countries with an agricultural dependence register increased exposure to climate risk. Turkey, which falls into the upper-middle-income country status according to the IMF statistics, can similarly be viewed as recording increased risk.

Turkey is exposed to elevated risk from many natural disasters, such as wildfires, floods, landslides, and droughts, because of its geographical position and economic structure, resulting in short-term economic costs. The World Bank's (2022) report on climate includes Turkey among the nations highly exposed to the impacts of climate change. The physical impacts of climate

change also encompass many challenges for Turkey with significant implications for its agricultural sector, food availability, infrastructure, and overall production.

In evaluating transition risk, it is evident that Turkey is highly exposed to climate-related risks. Its reliance on fossil fuels for most of its power generation exacerbates the risk for "stranded asset" scenarios in the event of a demand shock triggering a need for the imposition of stringent carbon regulation (Gulaydin and Mourshed, 2025). Additionally, over-reliance increases the banking and credit risk in fossil fuel investment. Through the inclusion of factors such as the cost of policies and carbon pricing in transition risk analysis, it becomes clear that Turkey is highly exposed to climate risk at both the macroeconomic and firm levels. It requires the development of new policy proposals that yield tangible outcomes.

The overall analysis demonstrates that the impact of climate change has various economic implications, such as the costs of manufacturing and supply systems. This evidence demonstrates that climate change may influence the operations of companies and their financial results in a limited manner and also generate larger economic hazards. Thus, it is evident that climate risk is also a business financial risk and not solely an environmental risk.

Dividing the analysis of the impact of climate risk on the economy into two will help understanding. Dividing it this way allows us to consider the various sectors and aspects impacted by climate risk at a broad level and a detailed level. Climate change risk impacts several major economic factors (Houari et al., 2025). A few of the most significant factors are economic growth, financial stability, inflation, and energy consumption. The negative effects of climate change risk on energy consumption affect many sectors, particularly the transport sector (Cutcu et al., 2023) and manufacturing. Furthermore, recent research reveals a measurable negative relationship between financial stability, inflation variables, and climate change risk (D'Orazio, 2025; Qi et al., 2025).

Climate risk negatively impacts countries' sovereignty, stock market performance and competitiveness to a certain extent (Barbu et al., 2022). Therefore, climate change risk affects many important macroeconomic variables, including economic growth and competitiveness. Furthermore, research suggests that climate change risk can hinder socioeconomic progress (Huang et al., 2023). However, the impact of companies as microeconomic actors on climate change has received relatively little attention compared to that of macroeconomic factors.

Many studies in the literature examine the impact of climate risk on firm value, the cost of capital, investment decisions, and profitability. Some of these studies focus on the impact of climate change risk on corporate environmental, social and governance (ESG) performance (Wright and Nyberg, 2024; Khalid et al., 2024; Abdulla and Jawad, 2024; Li et al., 2024; Yin et al., 2024; Li and Zha, 2025; Afzali et al., 2025), while others have explored the impact of climate change risk on the green and technological innovation achievements of companies (Zhao and Parhizgari, 2024; He et al., 2024; Habib et al., 2025). Apart from this, studies have also been conducted on other major issues such as firm value and company risk (Lu et al., 2024; Xing et al., 2024; Abd-Elhaleim et al., 2025; Chen and Wang, 2025).

Several studies tested the effect of climate risk on the financial performance of companies (Huang et al., 2018; Sun et al., 2020; Cavlak et al., 2021; Mondal and Bauri, 2022; Zhang et al., 2023; Ozkan et al., 2023; Sun et al., 2023; Dinh et al., 2024; Fazil et al., 2024; Mondal and Bauri, 2024; Thai et al., 2024; Bauri et al., 2025; Khemiri et al., 2025). However, the majority of these

studies focus on companies operating in developed countries. In developing economies, the effects of climate risk may emerge through different channels due to differences in the depth of financial systems, corporate governance structures and regulatory frameworks. Although there are studies on the interaction between high-carbon emission sectors, capital markets, and sustainability policies in energy-intensive, externally dependent economies such as Turkey (Kolsuz and Yeldan, 2017; Kılıç et al., 2018; Kılıç and Kuzey, 2019a; Kılıç and Kuzey, 2019b; Gahramanova and Furtuna, 2023; Öncel and Akbulut, 2024), the impact of climate risk on firm performance has not yet been adequately investigated. This creates a significant empirical gap in the literature. In this context, the main research question can be expressed as follows:

“How and through what channels does climate risk affect corporate profitability in an emerging market environment?”

This study empirically examines the impact of climate change on the financial performance of firms operating in Turkey, addressing this gap. Moreover, it advances the understanding of the impact of climate risk on the performance of corporations through the adoption of an original climate risk scale developed by Bua et al. (2024). The research used panel data collected from corporations listed in the Borsa Istanbul (BIST) Sustainability 25 Index during the years 2005 to 2023. The corporations in question are characterized by clear disclosures concerning their environmental and governance approaches, and hold distinctive institutional capacities to respond to climate risk.

While estimating the impact of climate risk on financial performance, it is necessary to account for dynamic relationships and the presence of potential endogeneity. Profitability in the firm is dependent on past performance and may have a bidirectional relationship with the climate risk indicators. Thus, the System GMM approach proposed by Blundell and Bond (1998) was chosen for estimation. The approach addresses the problem of endogeneity by including the level and the first-difference equation in such a manner that, with instrumental variables, consistent and efficient estimates can be derived. The model may then be used to quantify the impact of climate risk on short- and long-term profitability.

It explores the intersection between corporations' financial performance and climate-associated risk, and makes three novel contributions to the existing scholarship. It is the first empirical analysis of how climate risk impacts the financial results of Turkish companies using the System GMM technique in conjunction with the global risk scale used by Bua et al. (2024). Secondly, the research uses the dynamic panel model in order to accommodate the impact of past profitability and the endogenous variables, and thus allow for more reliable causal inferences concerning the impact of climate risk. Finally, the findings provide evidence to policymakers in the development of sustainable finance policies and the effectiveness of green investment policies in Turkey, offering empirical support in this area.

In order to be able to make these contributions, the second phase of the study shall be carried out in the following steps. A comparison of the latest scholarly publications is provided, and research hypotheses will be presented in the second section. The methodology and data set are explained in the third section. The fourth section of the study reports the research findings and discusses them in the context of earlier research. The conclusions, policy implications, limitations of the study, and avenues for future studies are contained in the final section.

2. Literature Review

Climate change has various direct and indirect effects on living beings, the environment, countries, and financial and non-financial institutions. Therefore, it is critical to analyses these impacts from multiple perspectives, present the findings, and develop policies to address these challenges. The literature offers a wide range of studies examining the economic consequences of climate change through macroeconomic indicators and microeconomic variables at the firm level. However, establishing a theoretical link between macroeconomic and microeconomic levels to explain how climate risk is transmitted would also enhance the internal consistency of the literature. This section therefore, examines the literature in three main areas to provide the basis for research hypotheses: 1) macroeconomic-level impacts, 2) firm-level responses, and 3) implications for financial performance.

2.1. The Impact of Climate Risk at the Macroeconomic Level

Macroeconomic research shows that climate risk affects countries' economic growth, financial stability, and price dynamics. Barbu et al. (2022), for example, define climate risk as a variable affecting countries' sovereignty risk, while Cutcu et al. (2023) point out that climate risk can significantly impact energy consumption. Hu and Borjigin (2024), meanwhile, argue that energy markets are more sensitive to climate risk during periods of economic change.

There are also studies in the literature that empirically examine the impact of climate change risk on financial stability and inflation (D'Orazio, 2025; Qi et al., 2025). In addition to studies indicating that commercial credit use decreases in countries with high climate risk (Islam and Wheatley, 2020), some studies suggest that climate risk can increase demand in certain circumstances (Niu and Li, 2022). In this context, it has been demonstrated that climate risk affects real and financial balances via macro-level cost shocks (e.g., energy supply issues and production disruptions) and uncertainty channels.

2.2. Responses to Climate Change at the Firm Level

The way firms respond to climate change is crucial in transmitting macroeconomic shocks to the microeconomic level. They are reorganizing their risk-taking behaviors in order to address the growing risk of climate change (Chen and Wang, 2025), as well as develop resilience to shocks by controlling their asset-liability structures. Lu et al. (2024) and Li et al. (2024) found that climate change increases credit and liquidity risk, and Jin and Cairang (2025) provided evidence that climate risk contributes to higher price volatility.

Moreover, the association between corporate climate risk and social responsibility (Habib et al., 2025), along with the linkage between climate risk and ESG performance (Yin et al., 2024), is also slowly gaining prominence in research. Companies with strong ESG performance have lower costs of financing and higher market confidence (Abdulla and Jawad, 2024). Moreover, the empirical evidence reveals that the underperforming ESG organizations also significantly depend on short-term debt (Li and Zha, 2025). Overall, the evidence suggests that climate risk provides a transformative effect on the allotments of capital, financing structures, and policies involving the social responsibility of companies.

2.3. Consequences for Financial Performance

The impact of climate risk on financial performance, mediated by investors' perceptions and market conditions, has attracted significant academic attention. Adediran et al. (2024) revealed that green and mature stock markets can act as buffers against climate risk. Conversely, findings by Xing et al. (2024) suggested that the protective role may contribute to enhancing market contagion unintentionally. Furthermore, studies revealed that climate risk significantly impacts investment outcomes of firms (Arian and Naeem, 2025). Conversely, investment in FinTech is viewed as an advanced measure that mitigates the impacts of climate risk on the financial market (Yao and Yang, 2025; Chen and Zhang, 2025).

Most of the firm-level studies document that climate change has a detrimental impact on financial performance (Cavlak et al., 2021; Zhang et al., 2023; Ozkan et al., 2023; Fazil et al., 2024; Dinh et al., 2024; Bauria et al., 2025; Qiu et al., 2025; Khemiri et al., 2025; Khemiri, 2025). Conversely, some research documents positive findings regarding the effects of climate change in some industry lines such as power transmission and agriculture (Sun et al., 2023; Mondal and Bauri, 2024; Thai et al., 2024). These variations indicate that the effect of climate risk is industry- and region-specific.

While macro-level cost shocks impact corporations' cost structures through the channels of energy and production routes, these impacts are reflected in the financial results via capital allocation, financing strategies, and investment decisions at the firm level. The mechanism reveals that climate risk creates financial results through the cost allocation and perception channels. The prior research lacks adequate empirical studies that assess this chain holistically. This study offers an original contribution to the research literature by analyzing, through an original country panel, the effect of climate risk on financial results in the physical and transition risk dimensions. In line with this theoretical framework, the core hypotheses of the research are structured as follows:

H1: Climate risk negatively affects corporate financial performance.

H1a: Physical risk negatively affects corporate financial performance.

H1b: Transition risk negatively affects corporate financial performance.

H2: Climate risk concerns negatively affect financial performance.

H2a: Physical concerns negatively affect corporate financial performance.

H2b: Transition concerns negatively affect corporate financial performance.

3. Data and Methodology

Existing research indicates a potential interaction between climate risk and corporate performance. Within this framework, the persistence of profitability and the mechanisms through which climate risks influence corporate performance demonstrate a dynamic configuration, wherein historical performance informs contemporary results. Usually, the impact of climate risk on business develops over time rather than suddenly; this impact finds expression in financial performance with some delay. Hence, the dynamic panel estimator has also been utilized to account for this time-varying impact and, in the process, eliminate potential endogeneity complications.

3.1. Data

The research aims to measure the effect of global climate risk on the performance of Turkey-centered corporations listed in the BIST Sustainability 25 Index by deploying two different datasets. Compared with existing studies, the current research utilizes climate risk indices prepared by Bua et al. (2024) to set out climate change risk. The risk indices can be categorized into two basic groups: the Transition Risk Index (TRI) and the Physical Risk Index (PRI). Reuters' news articles are considered in the creation of the indices, and the data is continuously updated. When creating the PRI, news articles related to rising sea levels, thawing permafrost, floods, and adaptation measures were taken into account. When determining transition risk, regulatory climate news and news discussing the importance of technological developments in achieving a greener economy were considered. To determine physical risk and transition risk, the Physical and Transition Concern (TRC) series is first created. Therefore, four different time series emerge as measures of climate risk. Four different panel regression models were created using the PRI, TRI, Physical Concern (PHC), and TRC time series to analyze the effects of climate risk on corporate financial performance within the scope of this study. Regarding climate risk, data developed by Bua et al. (2024) and published on the website named "Lavinia Rognone-Library" were used. The same data can also be accessed at <https://www.policyuncertainty.com/>.

The second dataset used in the study consists of ratios derived from companies' financial data, collected via the Finnet database. The company-level data cover the period 2005–2023 for companies included in the BIST Sustainability 25 Index for which complete data is available. Return on Assets (ROA) and Return on Equity (ROE) are used as profitability variables in the study to measure the impact of climate risks on company performance. The ROA variable is used because it allows for the assessment of company profitability independently of capital structure (Penman, 2013) and it is one of the most important ratios for measuring asset utilization efficiency (Gitman and Zutter, 2015). The other profitability variable, ROE, is used because it is a central measure of the value created by the firm for its equity investors (Damodaran, 2012), and plays a critical role in understanding the profitability of resources (Higgins, 2012). Additionally, Chen et al. (2005) found evidence in their study that ROA and ROE are among the strongest indicators in financial performance analysis, particularly in emerging markets. Accordingly, this study, conducted specifically for Turkey, employed ROA and ROE as financial performance determinants.

Control variables are used in the study to reduce confounding effects between variables and increase the explanatory power of the model. Accordingly, Total Assets ($\ln ASSETS$) and Asset Growth (AS_{Growth}) were added to the models as growth variables, Current Ratio (CR) as a liquidity variable, Leverage (LEV) as a leverage variable, Fixed Assets Ratio (FAR) as an asset structure variable, and Turnover of Total Assets (TTA) as an efficiency variable. The abbreviations, explanations, and data sources for the variables used in the analysis are shown in Table 1.

Table 1. Explanations Regarding Variables Used in the Analysis

Dependent variable	Abbreviation	Description	Source
Return on Assets	ROA	Net Income / Total Assets	Finnet
Return on Equity	ROE	Net Income / Shareholders Equity	
Independent variable			
Transition Risk Index	TRI	Variables Related to Climate Risk	L R - Library
Physical Risk Index	PRI		
Transition Concern	TRC		
Physical Concern	PHC		
Control Variables			
Total Assets	lnASSETS	Natural Logarithm of Total Assets	Finnet
Current Ratio	CR	Current Assets / Current Liabilities	
Asset Growth	AS _{Growth}	Asset growth by period	
Leverage	LEV	Total Liabilities / Total Assets	
Fixed Assets Ratio	FAR	Fixed Assets / Total Assets	
Turnover of Total Assets	TTA	Net Sales / Total Assets	

3.2. Methodology

The Generalized Method of Moments is used to estimate parameters in statistical models. There are several advantages to using the GMM estimator for dynamic panel data models. The advantage of the GMM methodology is that it takes into account econometric problems encountered in models with lagged dependent variables, such as unobservable country-specific effects and the endogeneity of independent variables (Mhadhbi, 2014: 48; Ke et al., 2020: 10).

In dynamic panel data analysis, GMM can be applied in different ways based on different assumptions. Arellano and Bond (1991) emphasized that GMM management yields better results than other methods in cases involving normally distributed data, varying variance, and measurement errors, and recommended the Difference-GMM estimation method. Subsequently, the System-GMM method was developed by Arellano and Bover (1995) and Blundell and Bond (1998). System-GMM estimators apply the first difference transformation and utilize the lagged values of the endogenous variables in the first difference equations (Coşkun and Kök, 2011: 79-80; Aytürk and Yanık, 2015: 161). In this context, System GMM provides more reliable and efficient estimates due to its lower variance (Blundell and Bond, 1998:138).

In this study, the Two-Step System GMM model estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998) was chosen as the analysis method to examine the relationship between climate risk and firm performance. System-GMM applications become susceptible to potential fragilities in data sets with a small number of units of observation (N) and a large number of time periods (T). In particular, a rapid increase in the number of instrumental variables and small-sample bias can cause the Hansen test to lose its meaning (Arellano and Bond, 1991; Blundell and Bond, 1998; Windmeijer, 2005; Roodman, 2009a; Roodman, 2009b; Bun and Windmeijer, 2010). To prevent such methodological issues and enhance the robustness of the model, various precautions were taken in our analysis. During the analyses, the number of instruments was limited by applying the “collapse” command in Stata. This prevented both the instrument proliferation problem and the model from becoming over-identified. Furthermore, to correct downward-biased deviations, the adjustment proposed by Windmeijer (2005) was applied, thereby estimating unbiased standard errors. The Windmeijer (2005) adjustment was a decisive factor in choosing the Two-Step System-GMM estimator. Furthermore, for robustness checks, the models were also estimated using the Driscoll–Kraay standard error estimator and One-Step

System-GMM. The findings obtained with these methods are presented compared to the Two-Step System-GMM results. The relevant regression model is given in Equation 1.

$$y_{it} = \beta_0 + \beta_1 y_{i,t-1} + \beta_3 X_{it} + \gamma Z_{it} + \eta_i + \lambda_t + \mu_{it} \quad (1)$$

Here; y_{it} : represents the dependent variable (ROA / ROE), $y_{i,t-1}$: It represents a lagged value of the dependent variable, X_{it} : represents the independent variable (TRI/PRI/TRC/PHC), Z_{it} : represents the control variables (lnASSETS / CR / AS_{Growth} / LEV / FAR / TTA), η_i : refers to firm-specific effects that cannot be observed, λ_t : expresses effects specific to unobservable time, μ_{it} : refers to the term error.

The following models were created to measure the relationship between the ROA, the independent variable, and climate risk indicators.

$$\text{Model 1: } ROA_{it} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 TRI_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

$$\text{Model 2: } ROA_{it} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 PRI_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

$$\text{Model 3: } ROA_{it} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 TRC_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

$$\text{Model 4: } ROA_{it} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 PHC_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

The following models were created to measure the relationship between ROE, which is another independent variable used in the analysis, and climate risk indicators.

$$\text{Model 1: } ROE_{it} = \beta_0 + \beta_1 ROE_{i,t-1} + \beta_2 TRI_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

$$\text{Model 2: } ROE_{it} = \beta_0 + \beta_1 ROE_{i,t-1} + \beta_2 PRI_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

$$\text{Model 3: } ROE_{it} = \beta_0 + \beta_1 ROE_{i,t-1} + \beta_2 TRC_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

$$\text{Model 4: } ROE_{it} = \beta_0 + \beta_1 ROE_{i,t-1} + \beta_2 PHC_{it} + \beta_3 \ln ASSETS_{it} + \beta_4 CR_{it} + \beta_5 ASGrowth_{it} + \beta_6 LEV_{it} + \beta_7 FAR_{it} + \beta_8 TTA_{it} + \eta_i + \lambda_t + \mu_{it}$$

4. Research Findings

Before presenting the analysis results, this section provides descriptive statistics and correlation values for the dependent and independent variables used in the study. Table 2 shows the mean, median, skewness, kurtosis, maximum, minimum, values, and standard deviation statistics for the variables. According to the descriptive statistics presented in Table 2, the average ROA of the companies is 5.01%, while ROE is 14.22%. The ROA variable ranges from a minimum value of -0.1821 to a maximum value of 0.9451, while the ROE variable ranges from -2.1013 to 6.4515. Furthermore, the skewness for the ROA variable is 4.47, and the kurtosis is 38.76, while the skewness for the ROE variable is 7.11 and the kurtosis is 148.37. Overall, the high skewness and kurtosis values in climate risk and financial variables indicate that there are

significant differences in environmental and financial structures among companies. Additionally, information obtained from descriptive statistics indicates that during the period covered by the data set analysis, companies showed moderate profitability (average ROA of 5%, average ROE of 14%), moderate indebtedness (average LEV of 58%), and a reasonable liquidity ratio (average CR of 1.45).

Table 2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Median	Max	Skewness	Kurtosis
ROA	1368	0.0501	0.0757	-0.1821	0.0352	0.9451	4.4659	38.7576
ROE	1368	0.1422	0.3054	-2.1013	0.1099	6.4515	7.1100	148.3686
TRI	1368	-0.0047	0.0267	-0.0815	-0.0060	0.1250	1.2553	9.4675
PRI	1368	-0.0066	0.0201	-0.0493	-0.0085	0.0656	0.5490	4.2444
TRC	1368	0.0790	0.0287	0.0314	0.0791	0.2166	1.2509	8.1379
PHC	1368	0.0706	0.0211	0.0248	0.0698	0.1251	0.0559	2.8908
lnASSETS	1368	16.4068	1.6246	13.2781	16.1806	22.1407	0.6255	3.0059
CR	1368	1.4514	0.6211	0.4300	1.3100	5.3200	1.2812	5.7085
AS _{Growth}	1368	0.2911	0.4666	-0.5063	0.1837	6.2677	5.5829	52.8941
LEV	1368	0.5888	0.1836	0.1304	0.6139	0.9990	-0.2468	2.2005
FAR	1368	0.5325	0.1498	0.1375	0.5302	0.8702	-0.0438	2.1902
TTA	1368	1.0829	0.9067	-3.1500	0.8150	7.4600	1.7794	11.4607

Following the descriptive statistics for the variables is followed by Table 3, displaying the correlation matrix associated with these variables. The results of the correlation analysis presented in Table 3 show the associations between the study's variables. There was a positive association between ROE and ROA. The climate risk indicators TRI, PRI, TRC, and PHC revealed strong and positive associations with each other. Associations between climate risk variables and the profitability indicators were weak and mostly negative. When the control variables were tested, positive associations between TTA and AS_{Growth}, and the profitability indicators existed. Conversely, there is a negative association between LEV and ROA, indicating that higher indebtedness can decrease profitability. In general, though the climate risk variables are highly related to each other, their effect on profitability is weak. To prevent potential multicollinearity in the analysis, climate risk indicator variables were incorporated in different models.

Table 3. Correlation Matrix

	ROA	ROE	TRI	PRI	TRC	PHC	lnASSETS	CR	AS _{Growth}	LEV	FAR	TTA
ROA	1.000											
ROE	0.551	1.000										
TRI	-0.009	-0.020	1.000									
PRI	0.000	0.015	0.547	1.000								
TRC	-0.055	-0.036	0.925	0.562	1.000							
PHC	-0.042	-0.015	0.535	0.930	0.629	1.000						
lnASSETS	-0.009	0.131	-0.123	-0.030	-0.141	-0.087	1.000					
CR	0.060	-0.068	-0.012	-0.042	-0.004	-0.027	-0.194	1.000				
AS _{Growth}	0.387	0.249	0.058	0.144	0.053	0.095	0.320	-0.095	1.000			
LEV	-0.256	0.047	-0.045	0.009	-0.051	-0.013	0.404	-0.600	0.102	1.000		
FAR	-0.089	-0.156	-0.047	-0.055	-0.054	-0.055	-0.037	-0.141	-0.003	-0.235	1.000	
TTA	0.278	0.273	0.017	0.021	0.031	0.038	-0.103	-0.181	0.108	0.138	-0.403	1.000

If panel data model endogeneity is left unaddressed, then it's possible that coefficient estimates become inconsistent and biased. Specifically, in financial performance models, it's possible that a number of independent variables exist in a two-way causal relationship with profitability. Consequently, prospective endogeneity consequences have to be controlled in an

effort to confirm model findings. In dynamic models, the lagged value of the dependent variable and firm-level parameters often carry potential endogeneity risk. This is because these parameters can change simultaneously with profitability changes due to firm-level decisions. Therefore, in our models, LEV, AS_{Growth}, and CR have been potentially endogenously estimated. The instrumental variable (IV) approach was used to address endogeneity in the problem. The basic intuition behind this method is to reduce estimation bias by eliminating the correlation between the error term and independent variables. Therefore, the instrumental variables in the form of lagged variable values were taken and estimated via the System-GMM estimator.

After determining the endogenous-exogenous status of the variables, the analysis was performed. Tables 4 and 5 show the Driscoll–Kraay estimates for all models, the one-step System GMM results, and the two-step System GMM results when the dependent variable is ROA.

Table 4. Relationship between Climate Risk and ROA (Model 1 and Model 2)

Dependent Variable ROA	Driscoll–Kraay Estimates		System GMM (One-Step) ¹		System GMM (Two-Step) ²	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
ROA _(t-1)			0.268* (0.139)	0.283** (0.133)	0.287* (0.140)	0.314** (0.126)
TRI	-0.089 (0.062)		-0.184* (0.095)		-0.170** (0.071)	
PRI		-0.185** (0.082)		-0.321* (0.160)		-0.348** (0.165)
lnASSETS	0.011 (0.007)	0.011 (0.006)	0.010* (0.005)	0.009* (0.005)	0.007* (0.004)	0.007* (0.003)
CR	-0.014 (0.013)	-0.015 (0.013)	0.001 (0.010)	0.000 (0.010)	0.009 (0.012)	0.007 (0.011)
AS _{Growth}	0.053*** (0.018)	0.054*** (0.018)	0.048* (0.024)	0.050* (0.025)	0.060*** (0.019)	0.060*** (0.017)
LEV	-0.220*** (0.071)	-0.219*** (0.071)	-0.341** (0.158)	-0.314* (0.152)	-0.287** (0.119)	-0.247** (0.112)
FAR	-0.010 (0.078)	-0.012 (0.077)	-0.505*** (0.128)	-0.516*** (0.126)	-0.472*** (0.153)	-0.487*** (0.132)
TTA	0.025** (0.010)	0.025** (0.010)	0.005 (0.016)	0.004 (0.015)	0.002 (0.016)	0.001 (0.015)
Number of obs.	1368	1368	1350	1350	1350	1350
Num. of instr.			14	14	14	14
R-squared	0.3154	0.3170				
AR1			-2.24 0.025	-2.26 0.024	-2.17 0.030	-2.24 0.025
AR2			0.04 0.967	-0.12 0.904	0.08 0.934	-0.05 0.961
Sargan Test			4.43 0.618	3.25 0.776	4.43 0.618	3.25 0.776
Hansen Test			3.94 0.684	2.82 0.831	3.94 0.684	2.82 0.831
	Hansen test exc. group		2.14	1.53	2.14	1.53
Difference-in-Hansen	Diff. (null H = exogenous)		0.829	0.910	0.829	0.910
			1.80 0.180	1.29 0.255	1.80 0.180	1.29 0.255

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1 level is significant.

¹ Obtained using Stata's "xtabond2" command with the "small onestep robust" option.

² Windmeijer (2005) corrected Two-Step GMM standard errors obtained using the "small twostep robust" option in Stata's "xtabond2" command.

Table 5. Relationship between Climate Risk and ROA (Model 3 and Model 4)

Dependent Variable ROA	Driscoll–Kraay Estimates		System GMM (One-Step) ¹		System GMM (Two-Step) ²	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
ROA _(t-1)			0.279* (0.150)	0.292** (0.135)	0.287* (0.154)	0.305** (0.135)
TRC	-0.220** (0.078)		-0.319** (0.112)		-0.294*** (0.092)	
PHC		-0.282*** (0.090)		-0.398** (0.148)		-0.408*** (0.139)
lnASSETS	0.009 (0.007)	0.010 (0.006)	0.007 (0.005)	0.007 (0.005)	0.004 (0.003)	0.005 (0.003)
CR	-0.015 (0.013)	-0.015 (0.013)	0.000 (0.009)	0.000 (0.010)	0.007 (0.011)	0.006 (0.010)
AS _{Growth}	0.055*** (0.018)	0.055*** (0.018)	0.045** (0.022)	0.044* (0.023)	0.054*** (0.019)	0.052*** (0.017)
LEV	-0.222*** (0.071)	-0.219*** (0.071)	-0.305* (0.174)	-0.288* (0.157)	-0.230* (0.116)	-0.210* (0.109)
FAR	-0.017 (0.079)	-0.015 (0.076)	-0.498*** (0.120)	-0.515*** (0.121)	-0.446*** (0.144)	-0.473*** (0.126)
TTA	0.025** (0.010)	0.025** (0.010)	0.008 (0.015)	0.007 (0.015)	0.004 (0.017)	0.003 (0.015)
Number of obs.	1368	1368	1350	1350	1350	1350
Num. of instr.			14	14	14	14
R-squared	0.3216	0.3210				
AR1			-2.22 0.026	-2.25 0.025	-2.06 0.039	-2.12 0.034
AR2			-0.20 0.845	-0.34 0.735	-0.26 0.792	-0.45 0.650
Sargan Test			2.94 0.816	2.48 0.870	2.94 0.816	2.48 0.870
Hansen Test			3.48 0.746	2.41 0.879	3.48 0.746	2.41 0.879
		Hansen test excluding group	3.36	2.18	3.36	2.18
Difference-in-Hansen		Difference (null H = exogenous)	0.645 0.12 0.724	0.824 0.23 0.433	0.645 0.12 0.724	0.824 0.23 0.632

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1 level is significant.

¹ Obtained using Stata's “xtabond2” command with the “small onestep robust” option.

² Windmeijer (2005) corrected Two-Step GMM standard errors obtained using the “small twostep robust” option in Stata's “xtabond2” command.

Tables 4 and 5 present models examining the relationship between ROA and climate risk. Models 1 and 2 use TRI and PRI indicators, while models 3 and 4 analyze TRC and PHC variables. Three different estimation methods, Driscoll–Kraay, One-Step System-GMM, and Two-Step System-GMM, were used, and high consistency was observed in terms of the direction and significance of the results.

The findings generally reveal that climate risk indicators negatively affect profitability in all models. According to the Driscoll–Kraay estimation results in Table 4, although the TRI in Model 1 is not statistically significant, the PRI coefficient in Model 2 is -0.185 and statistically significant. This suggests that the vulnerability of companies to physical climate risks adversely

impacts their active profitability. This influence is particularly evident in the GMM estimations. In the One-Step System-GMM models, the TRI coefficient is -0.184 and the PRI coefficient is -0.321, both of which are negative and statistically significant. Conversely, in the Windmeijer-adjusted Two-Step System-GMM estimates, these figures are -0.170 and -0.348, respectively, also demonstrating statistical significance. These statistics go on to depict that climate risk in a systematic and permanent manner negatively impacts the profitability of businesses. Climate risk's negative influence on profitability obliges governments to intervene to promote widespread adoption of disaster-resilient infrastructure and to get businesses to adapt to climate risk.

Likewise, the findings presented in the case of Model 3 and Model 4 in Table 5 indicate that the variables PHC and TRC significantly adversely affect ROA. The Driscoll–Kraay estimates yielded coefficients of -0.220 for TRC and -0.282 for PHC. These coefficients are statistically significant. It emerges that organizations' worries regarding the transition process and actual effects related to climate change have been stressing financial performance. In the One-Step System-GMM models, the coefficients for TRC (-0.319) and PHC (-0.398) are negative and significant. These calculated values were -0.294 and -0.408, respectively, in the Two-Step System-GMM method estimate, with the retention of the original sign and effect significance. These results unambiguously confirm that both transformational risks and regulatory risks related to the climate transition and physical climate threats have a constant and negative impact on operating profitability. Such findings corroborate the prevailing academic discussion (Cavlak et al., 2021; Zhang et al., 2023; Ozkan et al., 2023; Fazil et al., 2024; Dinh et al., 2024; Bauri et al., 2025; Qiu et al., 2025; Khemiri et al., 2025; Khemiri, 2025). It calls for the framing of climate policies in a more stable context and entails the adoption of prudent supporting measures, including tax relief to corporations.

Lagged variables in the models were also used in the current study, knowing that the effects of climate risk could be revealed over time. It then became possible to examine the effect of both current and prior period risks on firm performance. This approach enabled the use of the dynamic structure of the model. In all the models, the coefficient of the lagged dependent variable (ROA_{t-1}) was found to be positive and significant. The implication is the persistence of the measure of profitability ratios of firms, such that the prior period's performance has a positive effect on the current period's profitability.

After observing the control variables, the results show that the AS_{Growth} variable has a positive and highly significant correlation in all the models. This implies that accelerated growth culminates in higher profitability. The LEV variable was negative and significant. It was established that increased debt hampers the financial flexibility of firms and therefore reduces profitability. The FAR variable is considered insignificant in view of the Driscoll–Kraay estimation results, but it registered a negative and significant correlation in both the One-Step System-GMM and Two-Step System-GMM estimations. This indicates that capital-based structures limit profitability. The CR variable is found to be statistically insignificant and is viewed as not contributing to explaining profitability.

Estimates regarding the validity and reliability of the models yield significant results. The validity of the models presented in the form of estimates in Tables 4 and 5 was obtained using AR (2) together with the Hansen and Sargan tests. The model's autocorrelation was tested using the Arellano-Bond (1991) Serial Correlation Test. The absence of second-order serial correlation in this test is crucial for the consistency of the GMM estimator (Farzana et al. 2024: 5). Since the

p-values for the AR (2) parameter are greater than 10% in all models, the null hypothesis that there is no second-order autocorrelation cannot be rejected. Therefore, it indicates that there is short-term continuity in firm performance, but no serial correlation in the model. It also implies that the lagged dependent variable captures the performance dynamics in firms, as well. Examination of the results of the Hansen (1982) test shows that the p-values are higher than 0.05, implying statistical insignificance in all the models. Similarly, the analysis of the Sargan test statistics also indicates p-values higher than 0.05, implying statistical insignificance in all the models. The implication of this is that the instrumental variables used in the analysis are valid, and the null hypothesis that the instruments used in the model are exogenous cannot be rejected. Additionally, the findings of the Difference-in-Hansen test also support the exogeneity assumption of the instrumental variables used in the analysis. This implies that the instrument structure of the model is sufficiently defined and the GMM estimates are valid. Consequently, the assumptions underlying the System GMM hold.

The combined findings across the four analytical models confirm that climate risk has a negative impact on the financial performance of companies. The fact that similar results are obtained under different estimation methods indicates that this effect is not a temporary situation and represents a significant and sustainable source of financial vulnerability for companies. Specifically, the observed coefficients for physical risk are both larger and more statistically significant, indicating that corporations suffer more when they encounter environmental catastrophes like flood and storm damage. Conversely, transition risk negatively impacts profitability due to higher costs, regulatory pressures, and investment mismatches in the course of transitioning to the low-carbon economy. The repeated appearance of similar findings across several estimation procedures fortifies the view that the negative impacts of climate risk on financial performance are inherently structural and lasting in their effect, and thus confirms that climate risk presents an enormous cause of financial vulnerability for corporations.

However, because ROA used as the dependent variable is measured by total assets and is an indicator of performance, it may or may not respond directly and significantly to changes in capital structure. Especially, debt increases may be observed in the ROA to a limited degree, and the impact in some instances may be weak or indirect. Hence, in determining the impact of climate risk on ROA, the structural features of the indicator should be considered, and the findings should be interpreted carefully. This emphasizes the necessity of models that investigate the connection between capital structure and funding conditions, and ROA in more detail. In addition to this, the impacts generated by climate risk must be evaluated in terms of both the present balance sheet composition and future progress. A deterioration of a few percentage points in profitability can impact the investment capacity of companies, long-term growth possibilities, and financial flexibility, particularly in sectors with low profit margins and high competition. This can generate chain impacts on financial stability in the form of heightened risk perceptions in markets, elevated costs of borrowing, and deterioration in firm value. Therefore, such effects are not limited to performance indicators but constitute an issue that must be addressed at a strategic level for the long-term sustainability of firms.

When the findings are evaluated specifically for Turkey, it can be said that the ROA of companies included in the index is vulnerable to climate shocks. In particular, physical asset damages not covered by insurance, and the impact of climate shocks on balance sheets, may become permanent. Turkey's carbon-intensive energy structure increases the negative elasticity of ROA to climate shocks. Furthermore, the findings show that as climate risk is priced in by

lenders in Turkey, financing costs will increase and ROA will decline further. Additionally, credit restrictions on carbon-intensive sectors will increase the risk of negatively affecting ROA. Finally, physical risks such as forest fires and drought are also expected to have adverse effects on the supply chain.

After presenting findings on the effects of climate risks across all assets, an ROE analysis, which also evaluates the effects of climate risks in terms of financial leverage, will yield useful results. In this context, Tables 6 and 7 present the Driscoll–Kraay estimates, One-Step System GMM, and Two-Step System GMM Estimation Results for all models where the dependent variable is ROE.

Table 6. Relationship between Climate Risk and ROE (Model 1 and Model 2)

Dependent Variable ROA	Driscoll–Kraay Estimates		System GMM (One-Step) ¹		System GMM (Two-Step) ²	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
ROE _(t-1)			0.273*** (0.073)	0.257*** (0.076)	0.210** (0.084)	0.208** (0.080)
TRI	-0.255 (0.193)		-0.592** (0.227)		- (0.288)	
PRI		-0.227 (0.249)		-0.705 (0.461)		-1.073** (0.430)
lnASSETS	0.038** (0.015)	0.039** (0.015)	0.007 (0.019)	0.004 (0.018)	0.018 (0.012)	0.015 (0.010)
CR	-0.034 (0.025)	-0.034 (0.025)	0.038 (0.023)	0.034 (0.024)	0.023 (0.025)	0.015 (0.025)
AS _{Growth}	0.095*** (0.031)	0.095*** (0.032)	0.150* (0.073)	0.168* (0.081)	0.177*** (0.061)	0.195** (0.068)
LEV	-0.245* (0.127)	-0.242* (0.127)	-0.596 (0.481)	-0.614 (0.505)	-0.865* (0.473)	-0.926* (0.465)
FAR	-0.224 (0.191)	-0.220 (0.187)	-0.926* (0.495)	-0.942** (0.474)	- (0.405)	- (0.371)
TTA	0.128** (0.228)	0.128** (0.049)	0.050 (0.058)	0.047 (0.055)	-0.012 (0.044)	-0.011 (0.042)
Number of obs.	1368	1368	1350	1350	1350	1350
Num. of instr.			14	14	14	14
R-squared	0.1463	0.1460				
AR1			-1.28 0.199	-1.25 0.212	-1.35 0.178	-1.30 0.192
AR2			-1.12 0.265	-1.15 0.249	-1.18 0.237	-1.21 0.227
Sargan Test			14.96 0.021	14.90 0.023	14.12 0.015	13.68 0.018
Hansen Test			7.02 0.319	6.59 0.361	4.04 0.544	3.56 0.615
Difference-in-Hansen	Hansen test excluding group		5.90	6.26	3.73	3.16
			0.316	0.282	0.444	0.531
	Difference (null H = exogenous)		1.12	0.33	0.31	0.39
			0.290	0.567	0.578	0.531

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1 level is significant.

¹ Obtained using Stata's "xtabond2" command with the "small onestep robust" option.

² Windmeijer (2005) corrected Two-Step GMM standard errors obtained using the "small twostep robust" option in Stata's "xtabond2" command.

Table 7. Relationship between Climate Risk and ROE (Model 3 and Model 4)

Dependent Variable ROA	Driscoll–Kraay Estimates		System GMM (One-Step) ¹		System GMM (Two-Step) ²	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
ROE _(t-1)			0.279*** (0.072)	0.269*** (0.081)	0.216** (0.090)	0.197** (0.092)
TRC	-0.452** (0.181)		-0.535** (0.248)		-0.726*** (0.243)	
PHC		-0.525** (0.242)		-1.032** (0.414)		-1.358*** (0.425)
lnASSETS	0.037** (0.015)	0.038** (0.015)	0.008 (0.016)	0.003 (0.019)	0.018 (0.013)	0.008 (0.011)
CR	-0.035 (0.025)	-0.035 (0.026)	0.043* (0.024)	0.033 (0.025)	0.026 (0.024)	0.012 (0.026)
AS _{Growth}	0.098*** (0.032)	0.097*** (0.032)	0.137** (0.070)	0.171** (0.077)	0.169*** (0.057)	0.194*** (0.067)
LEV	-0.248* (0.127)	-0.243* (0.127)	-0.502 (0.512)	-0.612 (0.517)	-0.820 (0.498)	-0.931* (0.462)
FAR	-0.235 (0.188)	-0.229 (0.187)	-0.920* (0.503)	-0.987* (0.054)	-1.500*** (0.438)	-1.547*** (0.365)
TTA	0.129** (0.048)	0.129** (0.049)	0.055 (0.055)	0.057 (0.054)	-0.006 (0.050)	-0.004 (0.041)
Number of obs.	1368	1368	1350	1350	1350	1350
Num. of instr.			14	14	14	14
R-squared	0.1475	0.1471				
AR1			-1.24 0.215	-1.19 0.233	-1.27 0.203	-1.22 0.221
AR2			-1.22 0.224	-1.25 0.212	-1.20 0.232	-1.23 0.218
Sargan Test			14.55 0.012	13.53 0.019	14.55 0.012	13.53 0.019
Hansen Test			4.19 0.522	3.49 0.625	4.19 0.522	3.49 0.625
		Hansen test excluding group	3.88	3.08	3.88	3.08
Difference-in-Hansen		Difference (null H = exogenous)	0.423 0.31 0.576	0.545 0.41 0.522	0.423 0.31 0.576	0.545 0.41 0.522

Note: Standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1 level is significant.

¹ Obtained using Stata's “xtabond2” command with the “small onestep robust” option.

² Windmeijer (2005) corrected Two-Step GMM standard errors obtained using the “small twostep robust” option in Stata's “xtabond2” command.

The analysis results presented in Tables 6 and 7 demonstrate the impact of climate risks on ROE. According to the estimates of Model 1 and Model 2 in Table 6, climate risks appear to have a negative effect on ROE. According to the Driscoll–Kraay estimator, the TRI and PRI risk coefficients are not statistically significant. Looking at the System-GMM estimates, in a one-step estimation, the TRI coefficient is -0.592 and statistically significant, but the PRI coefficient is -0.705 and statistically insignificant. For Two-Step Windmeijer adjusted estimates, the coefficient estimates are calculated at values of -0.808 and -1.073 and are statistically significant. These results uncover that transition risks and physical risks put pressure on firms' long-run capital structure. Hence, such measures that facilitate financial assistance to firms in order to improve capital efficiency and bolster the environment of investment in Turkey should be taken.

Looking at the findings of Models 3 and 4 in Table 7, the TRC and PHC coefficients are negative and significant across all the models, indicating that the companies face financial fragility both during the process of transition and under the effect of direct environmental impacts. In the Driscoll–Kraay estimates, TRC is -0.452, and PHC is -0.525, and significant. In the One-Step System-GMM models, the TRC (-0.535) and PHC (-1.032) coefficients are negative and significant. In the Two-Step System-GMM models, the values of the coefficients are -0.726 and -1.358 and are statistically significant. Transition and physical risks of climate change lower the ability of corporations to make good use of their assets in generating profitability. Thus, it's worthwhile to utilize measures such as green financing incentives to minimize the uncertainties that corporations face and ensure equity profitability protection.

The highly significant and large coefficient for the lagged dependent variable ($ROE_{(t-1)}$) indicates continuity in the profitability model of enterprises. This finding indicates that companies that showed higher profitability during the previous periods maintained their performance, and hence the profitability dynamics showed a level of consistency.

In terms of control variables, AS_{Growth} is positive and highly significant in all models, showing that growing firms achieve a higher ROE. LEV is negative and significant, obtained from the Driscoll–Kraay estimates for all models. It is statistically negative and insignificant in the One-Step system GMM, while in the Two-Step system GMM, it is negative and significant only in models 2 and 4. The FAR variable is also negative and generally significant in all estimates except the Driscoll–Kraay estimates; this finding indicates that intensive investment in fixed assets weakens profitability. In contrast, CR is statistically insignificant in all models. While $\ln ASSETS$ is positive and statistically significant according to the Driscoll–Kraay estimates, it is, according to the other two estimators, statistically insignificant in all models.

For the model estimates presented in Table 6 and Table 7, since the p-values for the AR (2) parameter are greater than 10% in all models, the null hypothesis that there is no second-order autocorrelation is accepted. Therefore, there is no sequential autocorrelation problem in the model. The Hansen test results were statistically insignificant in all models and indicated that the instrument variables were valid. However, when we look at the Sargan test results, the p-values were statistically significant in all models. This result contradicts the Hansen test result and weakens the claim that the instrumental variables used are valid. However, a relatively large number of instruments in small samples can create such differences in results. Therefore, despite the significant results in the Sargan test and considering the more robust structure of the Hansen test, it can be said that the instrumental variables used in the models are consistent and valid overall. It increases the reliability of the estimation results and shows that the findings are supported methodologically, thus maintaining their general validity. The findings of the Difference-in-Hansen test also support the assumption of exogeneity of the instrumental variables used.

In general, findings from the four models show that companies' exposure to climate risk significantly reduces ROE. On the other hand, increases in debt levels create a leverage effect on ROE, amplifying the impact of climate risks on profitability and weakening companies' financial resilience. In this context, both forms of transition and physical risks (TRI–PRI and TRC–PHC) exhibiting negative effects reveal that companies are becoming vulnerable both during the transition process and in the face of direct environmental shocks. Furthermore, the findings are consistent with previous studies in the literature (Cavlak et al., 2021; Zhang et al., 2023; Ozkan

et al., 2023; Fazil et al., 2024; Dinh et al., 2024; Bauri et al., 2025; Qiu et al., 2025; Khemiri et al., 2025; Khemiri, 2025).

The permanent and adverse impact of climate risk on ROE could give rise to a number of macro-financial problems in countries such as Turkey, which have limited financial depth and are vulnerable to climate change. First, damage to physical assets caused by climate shocks will lead to capital erosion. Second, high climate risk will increase the risk premium for lenders and raise costs, resulting in lower returns on equity. Finally, the slowdown in capital accumulation due to climate risk may also have negative effects on the growth potential of companies and the economy. When the macro-financial impacts of the results are evaluated for Turkey, it is calculated that climate shocks would deter capital flows, escalate credit risk and collateral obligations, create falls in stock values, and adversely affect corporate transformation capacity by diminishing the funds dedicated to green transformation, because of weak ROE.

If the results are evaluated together, the findings indicate that climate risk has a detrimental impact on profitability-based measures of financial performance such as ROE and ROA. This implies a stronger and longer-lasting strain stemming from the channel of capital profitability. The current scenario also indicates that climate-associated factors can cause long-run damage to the sustainability of finance by perturbing the balance between the return on a firm's equity and its capital structure. The study finds that, just like the studied Turkish corporations, having high operating leverage in conjunction with low equity will further increase the level of financial vulnerability, given the future loss of equity stemming from a greater level of climate risk. Also, the scope of natural disaster insurance in Turkey is very limited, thus making it more likely that physical damage will be computed as a loss of equity. Given the sample companies' ESG integration activities, it is apparent that the problem is even greater for other companies.

5. Conclusion

This investigation analyzed the implications of climate-associated risks on the financial performance of corporations through the lens of dynamic panel data models. The analyses, which employed various estimation techniques (Driscoll–Kraay, One-Step, and Two-Step System-GMM), indicate that both physical and transition-related climate risks exert negative and statistically significant influences on corporate profitability. In this analytical framework, the effects of transition and physical risk indicators on ROA and ROE were assessed, demonstrating that environmental uncertainties present a financial challenge to enterprises. Escalating costs associated with climate change adversely affect corporate profitability. Notably, the negative and statistically significant effects of transition risk and physical risk indicators on both profitability metrics reinforce this observation. Moreover, the significance of lagged ROA and ROE values suggests that corporate profitability possesses a dynamic characteristic, wherein prior performance influences current profitability. Nonetheless, the findings also indicate that this effect diminishes over time. Concerning control variables, aspects such as firm size and asset growth are identified as factors that enhance profitability; conversely, elements like a high debt ratio and a considerable fixed asset ratio obstruct corporate performance. This situation emphasizes that the financial structures and investment strategies of firms can profoundly impact their capacity to endure climate risks.

The study also highlights the necessity for corporations to be proactive when it comes to managing risk from climate change and the role of policymakers in framing environments that

facilitate this. On the firm level, the evidence also advocates for the necessity of corporations to report climate risk accurately, which the regulatory architecture also must support. However, it is also found to be essential to develop policies for corporations based on not just the statements of sustainability but also quantifiable targets and impeccably implementable adaptation options related to the climate. The embedding of such policies by the organizations can go a long way in gaining a competitive advantage in areas where environmental concerns hold intense importance. Since the risk of climate change has the potential to negatively impact the valuation of corporations, it is essential to improve the availability of financial instruments like green bonds, sustainable debt instruments, and carbon markets for corporations to better handle the risk. The development of technical assistance and financial enabling programs, especially for the small and medium-sized organizations with severe debt burden and financial exposure, may be seen as part of the toolbox of policies aimed at improving their resilience in the face of climate-induced risk.

Following an analysis of the findings of the research at the policy-making level, it is apparent that specific sectoral and general instruments need to be applied in order to compensate for the impact of climate change among Turkish businesses. Notably, the immense costs that the energy-intensive industry incurs in transitioning to low-carbon production indicate the specific need for transition support at the policy-making level. In this context, it is imperative to create the financial and reporting infrastructure within a sustainable development process in the entire institutional setting in Turkey with the aim of encouraging active participation in green finance. Application of the policies will not only improve the capacity of companies to respond to climate-related risks but also enhance the resilience of the financial center to disruptions originating in climatic circumstances.

Based on comprehensive assessments and the analysis of Turkey's economic and institutional setting, it is necessary to spur investments to promote climate resilience among companies, as suggested by the findings in this study. In particular, it is necessary to strengthen insurance mechanisms in order to cushion the effects of climate risk on the equity and assets of companies. In addition to this, the shift towards sustainable finance also demands offering low-interest loans to companies displaying negligible carbon footprints. Rewards in the capital markets should be complemented by the provision of subsidies, such as tax breaks, to companies that are respectful of ESG principles. Supervisory and regulatory authorities, such as the Central Bank of the Republic of Turkey (CBRT), the Banking Regulation and Supervision Agency (BRSA), and the Turkish Banks Association (TBB), need to develop a macro-financial oversight framework that incorporates climate risk into their financial evaluations.

The research also identifies a few of its own constraints. Analysis is confined to the companies that are constituents of the BIST Sustainability Index. This restriction reduces the overall sample size. Future research that encompasses companies from various countries and industries will enable us to conduct comparison studies and derive greater policy implications.

Declaration of Research and Publication Ethics

This study, which does not require ethics committee approval and/or legal/specific permission, complies with the research and publication ethics.

Researcher's Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There is no potential conflict of interest in this study.

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THE IMPACT OF CLIMATE RESILIENCE ON BANKS' FINANCIAL STABILITY

İklim Dayanıklılığının Bankaların Finansal Sağlamlığı Üzerindeki Etkisi

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Abstract

The increasing volume of global trade driven by production and consumption following the Industrial Revolution has negatively impacted the socioeconomic environment. In response to climate risks, the globalized industry is seeking sustainable and green financial methods. For sustainable financial stability, climate change risks must be considered, and financial systems must limit their regulations within legal frameworks. In this context, the primary objective of this study is to examine the impact of countries' resilience and adaptation capacity to the adverse impacts of climate change on the stability of the banking sector. In the model constructed for this purpose, the bank Z-score is used as the dependent variable representing banks' financial stability, while the climate resilience index (CRI), carbon emissions (CO₂), economic growth (GDPG), economic freedom index (EFI), and political stability and absence of violence/terrorism (PS) are used as independent variables. The AMG test, a modern estimator that takes into account heterogeneity and cross-sectional dependence, was applied to a large panel of 96 countries. The analysis findings indicate that countries' resilience and adaptation capacity to climate change positively impact the stability of the banking sector. Economic growth has also been found to have an improving effect on the financial stability of the banking sector.

Keywords:

Climate Resilience,
Financial Stability,
AMG.

JEL Codes:

G20, G21, G28,
Q54, Q58.

Öz

Sanayi Devrimi'yle artan üretim ve tüketim kaynaklı küresel ticaret hacmi, sosyoekonomik çevre üzerinde olumsuz etkiler yaratmıştır. İklim risklerine yanıt olarak küreselleşen sanayi, sürdürülebilir ve yeşil finansal yöntemler aramaktadır. Sürdürülebilir finansal istikrar için iklim değişikliği riskleri göz önünde bulundurulmalı, finansal sistemler regülasyonlarını yasal çerçevelerle sınırlandırılmalıdır. Bu bağlamda çalışmanın temel amacı, ülkelerin iklim değişikliğinin olumsuz etkilerine karşı dayanıklılık ve uyum kapasitesinin bankacılık sektörünün istikrarı üzerindeki etkisini incelemektir. Bu amaç doğrultusunda kurulan modelde bankaların finansal istikrarını temsilen banka Z skoru bağımlı değişken olarak kullanılırken bağımsız değişken olarak da iklim dayanıklılık indeksi (CRI), karbon emisyonu (CO₂), ekonomik büyüme (GDPG), ekonomik özgürlük indeksi (EFI) ve siyasi istikrar ve şiddet/terörizmin yokluğu (PS) değişkenleri kullanılmıştır. Heterojenliği ve yatay kesit bağımlılığını dikkate alan modern tahmincilerden olan AMG testi 96 ülkeyi kapsayan geniş bir panel üzerinde uygulanmıştır. Analiz bulgularına göre ülkelerin iklim değişikliğine karşı dayanıklı ve hazırlıklı olma düzeyleri bankacılık sektörünün istikrarına olumlu yansımaktadır. Ekonomik büyümenin de bankacılık sektörünün finansal istikrarını iyileştirici bir etkiye sahip olduğu tespit edilmiştir.

Anahtar

Kelimeler:

İklim Dayanıklılığı,
Finansal İstikrar,
AMG.

JEL Kodları:

G20, G21, G28,
Q54, Q58.

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1. Introduction

Climate change refers to permanent shifts in global temperatures and weather patterns. While such changes can occur naturally due to factors such as solar fluctuations or large volcanic eruptions, they are currently largely the result of human activities. Climate scientists widely agree that impacts resulting from human action or inaction, particularly the widespread use of fossil fuels such as coal, oil, and natural gas, are the primary drivers of modern climate change. Over the past two centuries, the burning of these fuels has significantly increased greenhouse gas concentrations, leading to an unprecedented increase in global temperatures (United Nations, 2025). As climate experts emphasize, this phenomenon should not be viewed solely as an environmental problem. Rather, it represents a multifaceted challenge that interweaves environmental, economic, social, and political dimensions. The repercussions of a changing climate extend beyond natural ecosystems and extend to the very foundations of human activity. Key sectors such as manufacturing, energy production, agriculture, and supply chains are increasingly vulnerable to these changes. In this context, economic actors' operating conditions, investment decisions, and resource allocation strategies are increasingly affected by climate-related risks. These dynamics have the potential to exacerbate existing macroeconomic imbalances and increase the fragility of financial systems worldwide.

The potential for climate change to pose serious risks to macroeconomic and financial stability has been addressed by Dafermos (2018: 219) and Bölükbaş (2024: 159), who categorized these risks into three groups: physical risk, transition risk, and liability risk. Climate change manifests itself through a range of serious physical consequences, including drought, water scarcity, large-scale forest fires, rising sea levels, floods, melting polar ice caps, devastating storms, and biodiversity loss (NGFS, 2019). The direct and indirect impacts of these environmental changes on economic activity expose financial systems and the banking sector to physical risks.

In this context, according to the April 2019 report of the Network for the Greening of the Financial System (NGFS), it is particularly important to examine physical risks, defined as economic costs and financial losses arising from the increasing frequency and intensity of extreme weather events (such as heat waves, landslides, floods, forest fires, and storms) associated with climate change. This is because the slow progress of the transition to a low-carbon economy, spreading over years, will make steps to prevent severe global warming more difficult and will indirectly put stress on the resilience of financial systems. Such stress on financial systems will increase potential losses. In this context, which policies will be effective in reducing financial instability arising from the problems and damages caused by climate change can be determined by considering possible scenarios (Dafermos et al., 2018: 219). Moreover, the physical damages caused by climate change are not limited to production and supply shocks only; This could also lead to cascading effects such as declines in asset values, increases in credit default rates, and deterioration in the balance sheets of financial institutions. Therefore, maintaining the resilience of the financial system requires a joint assessment of climate risks within the framework of monetary policy, fiscal policy, and financial regulation.

In addition to physical risks, transformations in global policy and market dynamics in response to climate change can also create significant vulnerabilities for the financial system. Regulatory policies, energy price fluctuations, and technological innovations implemented during the transition to a low-carbon economy collectively reshape the structure of the

economy. During this process, firms operating in carbon-intensive sectors may experience declines in profitability, asset devaluations, and increased credit risk (Battiston et al., 2017). Consequently, rapid or unpredictable tightening of climate policies can lead to "transition risks," which can cause significant losses on financial institutions' balance sheets. Accurately assessing these risks is crucial for both maintaining financial stability and directing capital flows toward sustainable investments. Therefore, it would be beneficial to explain the scope, sources, and financial implications of transition risks.

Transition risk can be defined as a set of risks that emerge during the transition to a low-carbon economy and have the potential to impact both the financial system and the real sector. These risks stem from factors such as tightening climate policies, carbon pricing mechanisms, emissions regulations, the rapid adoption of new technologies, changes in consumer preferences, and evolving investor expectations (NGFS, 2019: 12).

The impact of transition risks on the financial system is particularly evident through sudden changes in the market valuations and profitability of firms operating in carbon-intensive sectors. Regulatory interventions in the energy, transportation, and industrial sectors during the low-carbon transition period can devalue certain assets, leading to losses on the balance sheets of banks and investment funds (Caldecott et al., 2016: 462–465). Furthermore, the increasing tendency of investors to adopt portfolio strategies based on Environmental, Social, and Governance (ESG) criteria is leading to a rebalancing of financial markets. This reallocation increases financing costs and magnifies credit risks for high-emission firms. Consequently, transition risks are gaining a systemic dimension, extending beyond specific sectors and impacting the entire financial system.

At the same time, the low-carbon transition is forcing companies and financial institutions to align their operations with international environmental standards and regulatory requirements. Organizations that fail to comply with climate policies may face reputational damage in the eyes of investors and public authorities, as well as legal liability under financial reporting standards and sustainability disclosure requirements (Campiglio et al., 2018). This suggests that physical and transition risks associated with climate change may gradually assume legal dimensions, giving rise to a new risk category: "liability risk."

Liability risk is defined as the possibility that organizations will face compensation claims or other legal action due to physical damage, environmental damage, or non-compliance with regulatory obligations resulting from climate change. Such risks are often considered a subcategory of physical and transition risks (NGFS, 2019: 12).

The transmission of physical risks to the financial system occurs through both macroeconomic and microeconomic channels, affecting firms, households, public authorities, and financial institutions (ECB 2021; ESRB, 2021: 10). Furthermore, efforts to prevent, mitigate, or adapt to climate-related risks can create new and significant transition risks and financial risks (Bernal and Ocampo, 2020: 9).

Climate-related risks translate into financial risks through risks within the financial system (BCBS, 2021; NGFS, 2019). Financial risks (ranging from credit risk, interest rate risk, exchange rate risk, liquidity risk, and market risk to capital adequacy risk) are inherent in the banking system and can be exacerbated by external shocks. These risks, if not mitigated, have the potential to destabilize globally interconnected financial markets (Yıldırım, 2020: 179–205).

The impact of climate-related risks on the financial system necessitates a reassessment of traditional risk categories. Climate change introduces a new and complex dimension that increases financial risks. While traditional causes of credit and market risks include economic recessions, interest rate fluctuations, or asset price declines, these risks are now increasingly shaped by climate events and environmental policies. While production and supply disruptions, particularly those resulting from physical risks, can lead to decreases in collateral value and weakening of borrowers' repayment capacity, transition risks can cause sudden losses in the balance sheets of firms operating in carbon-intensive sectors (Bolton et al., 2020). This suggests that the nature of financial risks is evolving and that climate factors are becoming a key determinant in macrofinancial stability analyses.

Furthermore, the financial system's exposure to climate risks extends beyond micro-level impacts on individual bank balance sheets; it also entails systemic contagion and spillover effects. Climate-induced shocks can propagate throughout the financial system through credit networks, securities portfolios, and capital flows (D’Orazio and Popoyan, 2019). Therefore, comprehensively integrating climate risks into traditional financial risk frameworks has become a critical imperative to enhance the resilience of the banking sector. Therefore, to maintain financial stability, banks must incorporate climate risks into their risk management, credit assessment, and capital adequacy practices.

The banking sector, a key pillar of capital allocation and risk management, is increasingly exposed to the multifaceted impacts of climate change. These risks can compromise asset quality, increase credit and market risks, and reduce profitability, threatening overall financial resilience. Both physical and transition risks have direct impacts on banks' balance sheets, loan portfolios, and risk management frameworks (Feyen et al., 2020; Cárdenas, 2024; Kum, 2025: 68). Beyond traditional credit risk, climate change can also have indirect impacts on bank balance sheets. If banks interact extensively with carbon-intensive sectors through their existing clients or projects, they may be unable to retire overdue loans, exposing them to reputational risk. In the long run, this could undermine both the stability of financial institutions and their liquidity positions (Sayıl and Atukalp, 2025: 877).

Extreme weather events such as severe droughts, floods, and devastating storms can disrupt economic activity and weaken borrowers' ability to repay their loans. Losses in key sectors such as agriculture, energy, and real estate can undermine financial stability by devaluing loan portfolios and eroding collateral. Meanwhile, rising sea levels and declining biodiversity pose risks of long-term asset devaluation and increased contingent liabilities within the financial system. Therefore, effectively measuring climate risks, integrating them into financial regulations, and adopting sustainable financing frameworks are critical to maintaining banking sector stability (NGFS, 2019; ECB, 2021; BIS, 2020)

To maintain the resilience of the financial system and ensure the stability of the banking sector, the European Union, together with other international organizations, has established a sustainable finance framework designed to mitigate emerging risks and increase market transparency. At the heart of this initiative is the EU Taxonomy Regulation, which serves as a classification system that defines criteria for economic activities that are climate-neutral and compatible with broader environmental targets by 2050 (European Commission, 2025). This regulatory framework, also known as the European Green Deal, facilitates the channeling of investments into activities deemed necessary to mitigate transition risks. The Taxonomy

provides a roadmap, particularly for the banking sector, to identify and evaluate companies making green investments (European Commission, 2025). In this context, the sector is expected to gain greater stability in financing sustainable activities. However, caution should be exercised in managing risks that may arise during the transition period.

The increasing visibility of climate risks and their impacts on the financial system has led regulatory authorities and policymakers to develop new frameworks aimed at preserving the sustainability of financial stability. In this context, reducing the vulnerability of the banking system to climate risks, restructuring risk management approaches in line with sustainability principles, and redirecting financial flows towards a low-carbon economy have become increasingly important. The European Union, in particular, along with various regional and international organizations, has adopted a comprehensive policy approach to limit the transmission channels of climate-related risks to the financial system. These approaches aim not only to increase transparency in financial markets but also to strengthen long-term stability by encouraging the allocation of capital to environmentally sustainable activities.

To this end, this study aims to empirically examine the impact of countries' resilience and adaptation capacity to the adverse impacts of climate change, measured by the ND-GAIN Country Index, on the stability of the banking sector. The motivation of this research is to quantify the impact of countries' resilience and adaptation capacity to climate change on the performance, risk structure, robustness, and stability of the banking sector.

Accordingly, the subsequent sections of the study are organized as follows: a review of the relevant literature and the study's contributions; a detailed explanation of the data set, variables, and methodology employed; empirical findings; and a concluding section with policy recommendations.

2. Literature Review

In recent years, numerous studies have examined the impacts of climate risks on the financial system, rapidly transforming the literature into a multifaceted field of research. These studies cover a wide range of topics, from conceptual foundations to empirical evidence, from policy frameworks to country-specific analyses. A comprehensive literature review shows that existing studies can be categorized under five main themes: (i) conceptual and theoretical approaches, (ii) the link between financial stability and monetary policy, (iii) empirical findings, (iv) studies focused on Turkey, and (v) policy recommendations and future research directions.

The theoretical foundations of the relationship between climate risks and the financial system were further clarified by Carney's (2015) groundbreaking speech. Carney categorized climate risks as physical, transition, and liability risks and described the financial system's tendency to ignore long-term risks as the "horizon tragedy." This perspective marked a turning point by emphasizing the need to restructure the financial system within a sustainability framework. Fabris (2020) highlighted the dual nature of climate change as both a threat and an opportunity, arguing that managing climate risks should be viewed as an integral component of financial stability for central banks and regulatory authorities. Similarly, Cardenas (2024) noted that existing climate risk models are inadequate, particularly for small and medium-sized financial institutions, and emphasized the need to strengthen risk modeling and data infrastructure. Collectively, these studies provide a conceptual foundation for understanding the

interaction between climate and finance and provide a theoretical basis for subsequent empirical analyses.

Climate risks have been a significant focus of research in the relationship between financial stability and monetary policy. Dafermos et al. (2018) argued that the physical and transition risks associated with climate change could lead to credit crunches and instability within the financial system, while "green quantitative easing" policies could mitigate these adverse effects. Bernal and Ocampo (2020) emphasized that financial policies should be supported by appropriate prudential frameworks to ensure that climate risks are accurately reflected in financial balance sheets. In the Turkish context, Karagöl (2022) argued that the central bank should integrate climate risks into monetary policy models and promote green financing instruments. In a comprehensive literature review, Zhou et al. (2023) found that natural disasters and physical risks negatively impact banking stability, insurance profitability, and capital flows, while strong regulatory frameworks help mitigate these effects. This study offers theoretical and institutional insights into the macrofinancial impacts of climate risks, particularly from a central banking perspective.

Empirical studies also aim to quantify the impact of climate risks on the financial system. Blickle et al. (2021) examined the impact of weather-related disasters on the financial performance of banks in the United States and found that such disasters are unlikely to undermine bank stability. They showed that such weather disasters are not a significant threat even to small-scale banks in the United States. U-Din et al. (2023) investigated the impact of extreme weather events on the Canadian banking sector. Based on the period from 1988 to 2019, this study found that extreme weather events did not have a significant impact on the Canadian banking sector. Berger et al. (2023) examined the impact of climate risks on the US banking sector. This study found that climate risks arising from extreme storms are a significant source of operational losses experienced by banks. Storms were found to increase the frequency of operational losses for banks and the likelihood of tail losses associated with financial stability. Noth and Schüwer (2023) examined the post-disaster stability of banks in regions affected by natural disasters, finding that banks' default probabilities, non-performing loan ratios, and foreclosure rates increased, while their z-scores, return on assets, and equity ratios decreased. In a panel analysis covering European countries, Caporale et al. (2025) found that carbon emissions negatively affected banking stability. Focusing on Türkiye, Turnacıgil (2025) found a unidirectional causality between physical climate risks and banks' stock returns. These findings provide empirical evidence that climate risks directly affect financial stability and highlight the sensitivity of the financial system to climate-related factors.

From an emerging economies perspective, research is increasingly focusing on Türkiye. Kılıç and Kuzey (2019) find that bank size, profitability, and publicly traded status increase the extent of climate-related disclosures. Aslan et al. (2022) showed that, following the Paris Agreement, Turkish banks reduced credit supply in provinces with higher pollution levels, suggesting they began to integrate climate risks into their credit policies. Çipe (2023) found no significant relationship between financial stress and environmental indicators, while Erdoğan (2024) emphasized that climate change necessitates a strategic transformation in the banking sector. Collectively, these studies offer unique national-level insights into how the Turkish financial system responds to climate risks.

The final body of work focuses on policy directions and future research gaps related to the effective management of climate risks. Carney (2015) and Bernal and Ocampo (2020) emphasized the importance of integrating climate risks into financial reporting and monetary policy processes, while Cardenas (2024) emphasized the need to improve data infrastructure and risk management capacity, particularly in smaller banks. Accordingly, the literature suggests that climate risks should not be viewed solely as environmental concerns but as systemic financial risks requiring comprehensive policy interventions.

Overall, the literature has evolved from theoretical foundations to empirical applications and from national case studies to broader policy recommendations. While early studies focused on developing conceptual frameworks, recent research has adopted a more holistic perspective encompassing financial stability, policy, and implementation dimensions. This evolution reflects the deepening of the climate-finance nexus and its transformation into an interdisciplinary field of research.

In this context, the current study addresses both environmental and financial vulnerabilities and includes countries that are party to climate agreements, along with Türkiye. Using a dataset covering the period 2006–2020, the study examines the impact of climate resilience and adaptation capacity on the financial stability of banks in both developed and developing countries, ensuring data consistency given the different timelines for agreement ratification. Furthermore, because the study uses a large panel of 96 countries, it analyzes the impact of climate resilience and adaptive capacity on bank stability while also accounting for spillover effects and classifying countries according to specific criteria. Therefore, it is expected to provide more comprehensive information than studies focusing on a specific country or group of countries. By analyzing the relationship between environmental factors, climate resilience, and financial stability across a broad set of countries, this study adds depth and richness to the literature and offers new perspectives for future research.

The study's findings are expected to contribute to banks' risk management, strategic planning, and corporate governance processes, and to inform policy development. It is also expected that the study will raise investors' awareness of the need to consider climate-related shocks in addition to financial risks.

3. Methodology

This study aims to empirically demonstrate the impact of countries' climate resilience and adaptation capacity on the financial stability of the banking sector from a global perspective. The study sample includes 96 countries (these countries are listed in footnote 2), and the period covers a fifteen-year period from 2006 to 2020. Based on the findings of this study, policy recommendations are presented for the integration of climate-related factors into banks' risk management methodologies. Therefore, the study is expected to provide strategic insights for policy makers, financial regulatory authorities, and banking sector managers.

3.1. Variables and Data Set

In the model established for the purpose of the study, the dependent variables are the bank Z-score (BANKZ), climate resilience index (CRI), carbon emissions (CO2), economic

growth (GDPG), economic freedom index (EFI), political stability/violence, and absence of terrorism (PS). These variables are explained below.

3.1.1. Banking Sector Stability

Due to its widespread use in the literature (e.g., Demirgüç-Kunt and Huizinga, 2010; Demirgüç-Kunt and Detragiache, 2011; Li et al., 2017; Goetz, 2018; Le et al., 2023), the BANKZ was chosen as the dependent variable representing the financial stability of the banking sector. Data on the BANKZ of the 96 countries included in the study were taken from the World Bank database. The Z-score is a measure, in standard deviations, of how much the return on assets must fall for a bank to reach the point of bankruptcy. In other words, the Z-score quantitatively expresses the distance between a bank's current financial condition and its default threshold (Demirgüç-Kunt and Huizinga, 2010: 628). A higher Z-score then indicates stronger financial stability and a lower probability of bank failure, and vice versa (Le et al., 2023: 5).

The Z score, which measures the buffer defined by the capital adequacy and return performance of a country's banking system according to the volatility of these returns, is calculated with the following formula¹:

$$Z = Ln[(ROA + (Equity / Assets)) / \sigma(ROA)] \quad (1)$$

3.1.2. Climate Resilience Index

The ND-GAIN score, developed by the University of Notre Dame to assess the country-level impacts of climate change, is widely used in academic literature (Ozkan et al., 2021; Cevik and Jalles, 2022; Gong et al., 2023; Lee and Alam, 2024; Wu et al., 2024). This score measures countries' vulnerability and readiness levels against climate change through a multidimensional framework. How the score measures these levels is explained below (ND-GAIN, 2024: 5-6).

Vulnerability reveals the level or tendency of societies' exposure to climate-induced threats. Six critical sectors are central to calculating each country's vulnerability: food, water, health, ecosystem services, human habitat, and infrastructure systems. Analysis is conducted for each sector through exposure, sensitivity, and adaptive capacity parameters. Exposure measures the level of pressure that future climate change conditions will create on society and supporting sectors; sensitivity measures the extent to which people and the sectors they depend on are affected by climatic disruptions; adaptive capacity measures the adjustment capacity that society and supporting sectors possess to reduce and adapt to the adverse effects of climate events.

Readiness measures countries' capacity to effectively utilize climate adaptation investments. This effectiveness is directly related to the existence of a safe and efficient business environment. Readiness level is evaluated in three subcategories. Economic readiness encompasses the investment environment that facilitates capital flow from the private sector; governance readiness covers social stability and institutional structures that determine investment risks; social readiness encompasses the social dynamics that enable society's capacity to use investments efficiently and equitably and the potential to derive optimal benefits from these investments.

¹ <https://databank.worldbank.org/metadataglossary/global-financial-development/series/GFDD.SI.01>

The ND-GAIN score calculated with Equation 2 is scaled between 0 and 100 (ND-GAIN, 2024: 11), with a high score indicating low climate risk (Wu et al., 2024: 5). In this context, it can be stated that countries with high ND-GAIN scores have a low tendency to be affected by climate change and are prepared against climate change.

$$ND - GAIN \text{ score} = (Readiness \text{ score} - Vulnerability \text{ score} + 1) \times 50 \quad (2)$$

3.1.3. Carbon Emissions

Carbon emissions, as a measure of countries' environmental performance, are considered among the factors affecting banking sector stability in the finance literature (Agbloyor et al., 2021; Ali et al., 2023; Ding et al., 2023; Masunda, 2025). Within the framework of stakeholder theory, Ali et al. (2023) state that efforts to reduce carbon emissions enable banks to develop strong relationships with different stakeholders (such as investors, regulators, depositors, and society). In this context, banks with low carbon emission scores are expected to evaluate climate risks more rigorously when lending, thus protecting stakeholder interests. This stakeholder-focused approach ensures that bank managers are more sensitive to carbon emission scores and related lending strategies, which contributes to strengthening banking stability (Ali et al., 2023: 2).

3.1.4. Economic Growth

Fluctuations in GDP growth rates create a systematic impact on the credit expansion process and the soundness of the financial system (Kum, 2025:67). Gross Domestic Product (GDP) growth rate is used as one of the main indicators of economic growth and is a widely used macroeconomic variable in the empirical literature on the determinants of banking sector stability (Demirgüç-Kunt and Detragiache, 2011; Kasman and Kasman, 2015; Chiaramonte et al., 2016; Ghenimi et al., 2017; Le et al., 2023; Yaseen et al., 2024). In the database provided by the World Bank, GDP is defined as the total income generated from the production of goods and services within a country's borders in a given period. It is calculated using three different methods based on expenditures, incomes, and production levels. The World Bank accepts the percentage change in GDP calculated at constant prices and expressed in US dollars compared to the previous year, using 2015 as the base year, as the GDP growth rate (World Bank, 2024). While examining the impact of countries' resilience and adaptation capacity to the adverse impacts of climate change on the stability of the banking sector, we consider that economic growth may also be affected by climate risks. However, within the scope of this study, economic growth is considered a secondary issue rather than the focus of the research. Therefore, our analysis primarily focuses on bank stability. A financially sound banking system generally indicates financial stability, and a stable financial environment provides the necessary foundation for sustainable economic growth. In this context, the economic growth variable is included in the model due to its potential impact from climate risks and its indirect relationship with financial stability.

3.1.5. Economic Freedom Index

The economic freedom index is also considered among the factors affecting banking sector stability (Asteriou et al., 2016; Mavrakana and Psillaki, 2019; Sarpong-Kumankoma et

al., 2020). The Heritage Foundation (2025) defines the concept of economic freedom as the control authority that individuals have over their own labor and property. In societies with high levels of economic freedom, individuals have the freedom to work, produce, consume, and invest. Governments in such societies allow the free movement of labor, capital, and goods and avoid forcibly restricting individual freedom beyond the limits necessary to protect and maintain freedom. Similar to the theoretical approach presented by Asteriou et al. (2016), this study also argues that a country's economic freedom level, measured by institutional transparency level and corruption level, will have an effect on banking sector stability.

3.1.6. Political Stability and Absence of Violence/Terrorism Index

According to the theoretical framework presented by Athari et al. (2023), bank fragility and profit volatility are directly related to risk factors stemming from political uncertainty. This uncertainty environment causes decision-makers in banks to be unable to properly evaluate the best investment opportunities and borrowers' creditworthiness. This can lead to banks becoming financially unstable. On the other hand, increasing domestic political risk creates significant concerns for banking sector stability. Such risk reduces investor confidence, destabilizes the regulatory environment, and weakens management and risk management procedures. For this reason, political stability or political stability and absence of violence/terrorism variables are included in analyses as a critical variable in studies addressing factors determining banking sector stability (Ozili, 2018; Al-Shboul et al., 2020; Djebali and Zaghdoudi, 2020; Athari et al., 2023; Shabir et al., 2024). In this study, the political stability and absence of violence/terrorism index, which measures risk perceptions regarding the possibility of terrorism as well as political instability, has been used as an independent variable. Definitions, units, and data sources for all variables used in the study are included in Table 1.

Table 1. Description of Variables

Variable	Definition	Unit	Source
Dependent Variable			
ZSCORE	Banking sector stability index	Logarithmic index	World Bank, Global Financial Development
Independent Variable			
CRI	Climate Resilience Index (A higher score indicates lower climate vulnerability and higher climate preparedness, indicating stronger overall climate resilience. In other words, as a country's ND-GAIN score increases, its climate risk level decreases.)	0-100 points	ND-GAIN
GDPG	Real economic growth rate	Percentage (%)	World Bank
CO2	Annual CO ₂ emissions	Million Tons	Our World in Data
EFI	Economic freedom index	0-100	Heritage Foundation
PS	Political stability and absence of violence/terrorism	(-2,5) - (2,5)	World Bank, Worldwide Governance Indicators

Note: All variables have been transformed into their logarithmic form.

The ND-GAIN index is a global, free, open-source index that measures a country's current vulnerability to climate disruptions and assesses a country's readiness to leverage private and public sector investments for adaptation actions (IMF, 2024).

3.2. Analytical Method

This study utilizes panel dataset with annual frequency, covering 96 countries² over the period 2006–2020. Although the initial data collection aimed to span the years 1995–2024, the analysis period was ultimately restricted to 2006–2020 to ensure the inclusion of the largest possible cross-country sample with uninterrupted data availability. This decision ensures data integrity, enhances the reliability of the empirical results, and enables the construction of a balanced panel structure.

To address skewness in the distribution of the variables and allow for greater interpretive flexibility in the regression analysis, all variables were log-transformed, following the log-log modeling approach proposed by Wooldridge (2013).

During the data analysis process, descriptive statistics for the variables were first obtained. The Pearson Correlation Coefficient Test was then applied to determine the strength and direction of the linear relationship between the variables, and the Variance Inflation Factor test was applied to determine the presence of multicollinearity among the variables.

In the next step, the cross-sectional dependence (independence) of the variables was determined in order to decide on the test to be used to determine the stationarity levels. Due to the cross-sectional dependence in the variables, stationarity levels were determined using the CIPS statistic, a second-generation unit root test.

The cross-sectional dependence (independence) of the model was tested using the Pesaran (2004) CD test, homogeneity using the Pesaran and Yamagata (2008) delta test, and cointegration in the model using the Westerlund (2007) test. Following the cointegration test, long-term coefficients were estimated using the AMG method due to the heterogeneity problem and cross-sectional dependence.

The steps of the analysis process are illustrated below (See Figure 1).

² The 96 countries used in the study are as follows: Albania, Algeria, Angola, Armenia, Australia, Austria, Azerbaijan, Bahrain, Bangladesh, Belarus, Belgium, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Cambodia, Cameroon, Canada, China, Costa Rica, Cote d'Ivoire, Croatia, Cyprus, Czech Republic, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Georgia, Germany, Greece, Guyana, Haiti, Honduras, Hungary, India, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kyrgyz Republic, Latvia, Lebanon, Lithuania, Luxembourg, Malawi, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Nicaragua, North Macedonia, Norway, Oman, Pakistan, Panama, Paraguay, Philippines, Poland, Portugal, Romania, Russia, Rwanda, Saudia Arabia, Senegal, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Thailand, The Bahamas, Türkiye, Ukraine, United Kingdom, United States of America, Vietnam, Zambia.

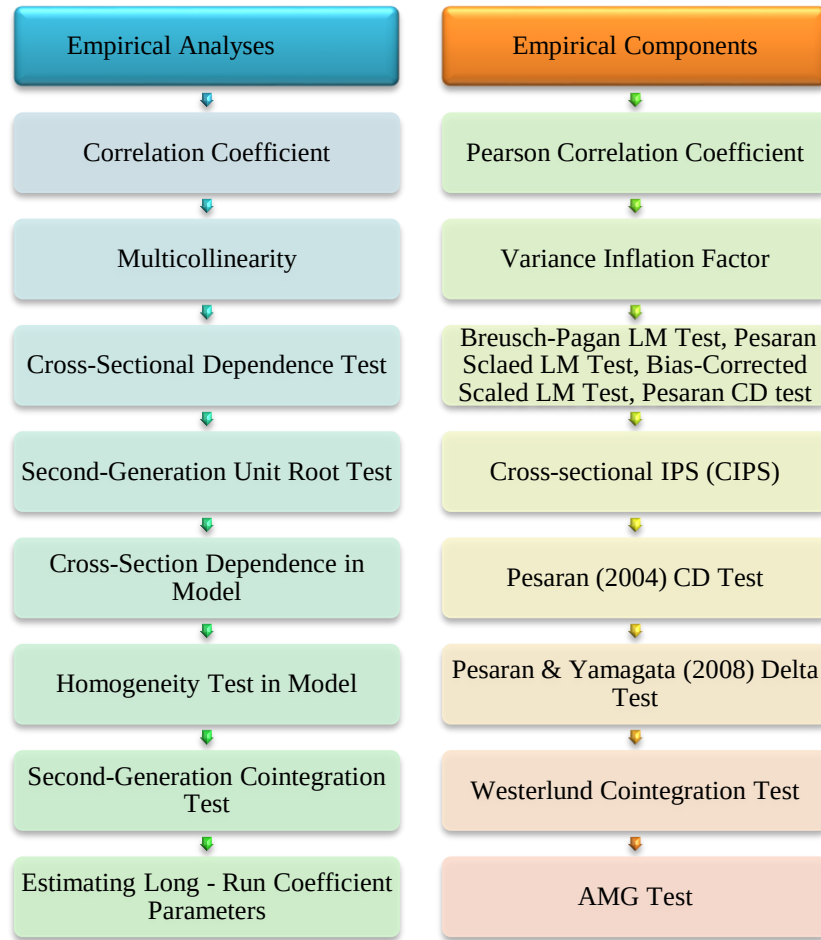


Figure 1. Analysis Process Steps

3.3. Results

In this section, the findings of the tests applied in Figure 1 and the evaluations related to these findings are given, respectively.

3.3.1. Descriptive Statistics

Descriptive statistics for the variables used in the study were calculated, and the results are presented in Table 2. The analysis covers 1440 observations from 96 countries over a 15-year period. When examining the findings related to the descriptive statistics of the data set, it is observed that the sample meets the required level of variability for the analysis and that there are no extreme outliers.

Table 2. Summary of Statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max.
BANKZ	1440	1.184272	0.2438428	-0.1713233	1.827822
CRI	1440	1.700537	0.0986242	1.496007	1.893846
GDPG	1440	1.389856	0.0996731	-0.2217761	1.816106
CO2	1440	7.61096	0.8760873	5.711315	10.03765
EFI	1440	1.799216	0.0625295	1.62634	1.951338
PS	1440	0.4523916	0.1574944	-0.7213275	0.6626752

3.3.2. Pearson Correlation Coefficient

The Pearson correlation coefficient is used to calculate the strength of the linear relationship between two variables. This coefficient, which can take values between -1 and +1, indicates whether the correlation between two variables is positive or negative. A positive coefficient sign indicates a positive correlation; if it is negative, it is considered that there is a negative correlation (Sedgwick, 2012: 1).

Table 3. Pearson Correlation Coefficient

	BANKZ	CRI	CO2	GDPG	EFI	PS
BANKZ	1.0000					
	-					
CRI	-0.0204	1.0000				
	0.4394	-				
CO2	-0.0583**	0.4567*	1.0000			
	0.0269	0.0000	-			
GDPG	0.1003*	-0.1878*	-0.0620**	1.0000		
	0.0001	0.0000	0.0186	-		
EFI	0.0903*	0.7589*	0.1387*	-0.1266*	1.0000	
	0.0006	0.0000	0.0000	0.0000	-	
PS	-0.0025	0.5764*	-0.0082	-0.0957*	0.5631*	1.0000
	0.9246	0.0000	0.7545	0.0003	0.0000	-

Note: * and **, respectively, denote significance levels of 1% and 5%. In addition, probability values are also included below the correlation coefficients.

Table 3 shows the strength of the linear relationship between variables using the Pearson correlation coefficient. A negative and weak correlation ($r = -0.0583$) was found between the BANKZ and CO2. Although the correlation coefficients indicate a negative and weak correlation ($r = -0.0204$; $r = -0.0025$, respectively) between the BANKZ and the climate resilience index (CRI), and political stability and absence of violence/terrorism (PS) variables, this relationship is not statistically significant. A positive and weak correlation ($r = 0.1003$; $r = 0.0903$, respectively) was found between the real economic growth rate (GDPG) and the economic freedom index (EFI) and the BANKZ. In summary, it is clear that the BANKZ variable has a significant but weak correlation only between CO2, GDPG, and EFI.

Correlation coefficients between independent variables reveal a moderately positive relationship between CRI and CO2 and PS ($r = 0.4567$; $r = 0.5764$, respectively). There is also a strong positive relationship between CRI and EFI ($r = 0.7589$), but a weak and negative relationship between CRI and GDPG. CO2 has a positive but weak relationship with EFI ($r = 0.1387$), and a negative and very weak relationship with GDPG ($r = -0.0620$). EFI and PS have a negative and weak/very weak relationship with GDPG ($r = -0.1266$; $r = -0.0957$, respectively), while EFI and PS have a moderate and positive relationship ($r = 0.5631$). Although there is a negative and very weak relationship between PS and CO2, the independent variables ($r = -0.0082$), this relationship is not statistically significant.

3.3.3. Variance Inflation Factor

Multicollinearity is often a problem in linear models, leading to unstable parameter estimates, loss of model reliability, and weakened predictive power. The Variance Inflation

Factor (VIF) was developed to address this issue (Cheng et al., 2022: 2). VIF shows the effect of other independent variables on the standard error of a regression coefficient and is directly related to the tolerance value (TOL) (Hair et al., 2019: 265).

$$VIF_i = \frac{1}{TOL_i} \quad (3)$$

Hair et al. (2019) state that if the VIF score is high, there is a multicollinearity problem and the commonly used threshold value is 10. Ramadan (2016) accepted the situation that the VIF score is below 5. Considering the sample size in the study, interpretation was made based on the VIF score being 5 or less.

Table 4. VIF Scores for Model

Variables	CRI	GDPG	CO2	EFI	PS
VIF Score	4.07	1.04	1.62	2.75	1.77

Note: The model's mean VIF is 2.25.

The highest VIF score in the model belongs to the CRI variable. Although this variable is moderately correlated with the other independent variables, a value below 5 does not pose a problem in modeling. The formulas for the model established within the scope of the study are given below.

$$BANKZ_{it} = \beta_0 + \beta_1 CRI_{it} + \beta_2 CO2_{it} + \beta_3 GDPG_{it} + \beta_4 EFI_{it} + \beta_5 PS_{it} + u_{it} \quad (4)$$

3.3.4. Cross-Sectional Dependence

Since the cross-section dependency test is decisive in the selection of the unit root test, the presence (absence) of the cross-section was tested before starting the analysis. To assess the presence of cross-sectional dependence among units in the panel data, four different tests for cross-sectional dependence were employed. This comprehensive testing strategy aims to mitigate the potential risk of relying solely on the outcome of a single test. The null hypothesis of these tests posits no correlation (cross-sectional dependence) among the units, while the alternative hypothesis assumes the existence of such dependence. The test statistics and corresponding p-values are reported in Table 5.

The results revealed that all variables, except for the PS variable, exhibited cross-sectional dependence across all four testing procedures. For the PS variable, only the Pesaran CD test fails to detect cross-sectional dependence among the units. However, due to different results obtained from the other three tests, we conclude that cross-sectional dependence also exists for the PS variable. In order to assess the stationarity properties of the variables appropriately, therefore, it is necessary to employ second-generation panel unit root tests that account for cross-sectional dependence.

Table 5. Findings of the Cross-Sectional Dependence Tests

Variable		Breusch-Pagan LM	Pesaran-scaled LM	Bias-corrected scaled LM	Pesaran CD
BANKZ	Test	13129.29	89.732	86.304	12.815
	Stat.				
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
CRI	Test	27349.53	238.637	235.209	63.704
	Stat.				
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
GDPG	Test	24560.55	209.432	206.004	135.236
	Stat.				
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
CO2	Test	24654.34	210.414	206.986	10.586
	Stat.				
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
EFI	Test	18936.03	150.536	147.108	17.393
	Stat.				
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
PS	Test	14014.05	98.997	95.568	0.885
	Stat.				
	p Value	0.0000*	0.0000*	0.0000*	0.3764

Note: *, denote significance levels of 1%.

3.3.5. Unit Root Test

Accordingly, the cross-sectionally augmented Im, Pesaran, and Shin (CIPS) panel unit root test was conducted to examine the stationarity characteristics of the variables. The results of this test are presented in Table 6.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_t - 1 + \delta_i \Delta \bar{y}_t + \sum_{j=1}^{pi} \phi_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (5)$$

where; Δ = the first-difference operator, y_{it} = the variable of interest for cross-section i at time t , $\bar{y}_t = 1/N \sum_{i=1}^N y_{it}$ = the cross-sectional mean at time t , α_i = individual intercept, β_i = coefficient testing for a unit root, γ_i , δ_i = coefficients that account for cross-sectional dependence, ε_{it} = error term. For each i , estimate the regression and obtain the t-statistic β_i . The CIPS statistic is then calculated as the simple average of the individual CADF statistics:

$$CIPS = 1/N \sum_{i=1}^N t_i \quad (6)$$

H_0 : All series contain a unit root; non-stationary.

H_1 : There is no unit root in at least one section in the series; stationary.

Table 6 presents the stationarity properties of the variables at levels and at first differences, evaluated at the 1% significance level. The notation $I(1)$ indicates that the variable becomes stationary after first differencing.

Table 6. Unit Root Test Results

Variables	CIPS Statistics I(0)	1% Critical Value	Stationarity I(0)	CIPS Statistics (1. Fark)	Stationarity I(1)	Results
BANKZ	-2.410	-2.42	✗ No	-3.247	✓ Yes	I(1)
CRI	-1.977	-2.42	✗ No	-3.247	✓ Yes	I(1)
GDPG	-1.959	-2.42	✗ No	-3.318	✓ Yes	I(1)
CO2	-1.925	-2.42	✗ No	-3.340	✓ Yes	I(1)
EFI	-2.103	-2.42	✗ No	-3.565	✓ Yes	I(1)
PS	-1.619	-2.42	✗ No	-3.552	✓ Yes	I(1)

3.3.6. Cross-Section Dependence and Homogeneity Test in Model

Determining the presence (or absence) of cross-sectional dependence in the model developed within the scope of the study is critical in selecting cointegration tests. Therefore, the model was subjected to the Pesaran (2004) CD test, designed to test cross-sectional dependence for large-N, small-T panels, as outlined by De Hoyos and Sarafidis (2006). The hypotheses for this test are given below.

H_0 : There is no cross-sectional dependence.

H_1 : There is cross-sectional dependence.

Pesaran and Yamagata (2008) stated that the Standard F test and the extended version developed by Swamy (1970) give appropriate results in panels where N is small compared to T, that Hausman-type tests, although applicable to large N panels, cannot give valid results in all cases and may cause the problem of low test power, and therefore, that there is no test that gives satisfactory results for slope homogeneity in panels where N is large compared to T. They proposed standardized distribution statistics that are asymptotically normally distributed as N and T go together to infinity. Considering the study's data set (N: 96, T: 15), the model's homogeneity test was performed using the Δ and Δ_{adj} tests suggested by Pesaran and Yamagata.

The Pesaran CD statistic is then calculated as:

$$CD = \sqrt{2T / N(N-1)} \left(\sum_{i=1}^{N-1} 0 \sum_{j=i+1}^N p_{ij} \right) \quad (7)$$

Pesaran and Yamagata standardized S as follows:

$$\Delta = [\sqrt{N(S - kN) / \sqrt{2kN}}] / 1 \quad (8)$$

Table 7. Cross-Section Dependence and Homogeneity Test in Model

Pesaran (2004) CD Test	Pesaran and Yamagata (2008)	
CD = 8.35	$\Delta = 11.844$	$\Delta_{adj} = 16.218$
p = 0.000	p = 0.000	p = 0.000

An examination of the analysis results in Table 7 reveals cross-sectional dependence and heterogeneity in the model. Given this finding, it is necessary to implement methods that can address the existence of cross-sectional dependence and heterogeneity.

3.3.7. Panel Cointegration Test

Since cross-sectional dependence (inter-unit correlation) was detected in the model, the Westerlund test, one of the second-generation panel cointegration tests that takes this feature into account, was used.

The cointegration test developed by Westerlund (2007) consists of four different parts: Ga, Gt, Pa, and Pt. The basic idea of this test is to determine whether individual panel members or the panel as a whole possess an error-correction mechanism and to test for the absence of cointegration. In the Ga and Gt statistics, rejecting the null hypothesis indicates cointegration in at least one of the cross-sectional units. In the Pa and Pt statistics, since the information on all cross-sectional units is tested by pooling, if the null hypothesis is rejected, it is understood that the panel is cointegrated as a whole. When applying the Westerlund cointegration test, if there is dependence between the units in the panel, critical values obtained from the bootstrap can be used instead of the standard critical values. Based on this, the findings of the Westerlund panel cointegration test are reported in Table 8.

Table 8. Westerlund Cointegration Test

Test	Test Statistics	Z-value	P-value	Robust P-value
Gt	-2.145	0.519	0.698	0.450
Ga	-2.482	11.793	1.000	0.000*
Pt	-18.610	-0.143	0.443	0.180
Pa	-2.178	7.213	1.000	0.100***

Note: * and ***, respectively indicate the significance levels of 1% and 10% .

When the panel cointegration test results applied to the model by Westerlund (2007) are examined in Table 8, the robust p-value of the Ga test obtained with the bootstrap in the first model is 0.000 (significant at the 1% level), indicating a cointegration relationship in at least one cross-sectional unit. However, the Pt test (robust p=0.180) showed no cointegration across the panel, while the Pa test (robust p=0.100) showed weak cointegration across the panel. Therefore, it can be said that the cointegration in the model is unit-specific. Since there is a cointegration relationship in the model, long-term coefficients were estimated with AMG.

3.3.8. Estimating Long-Run Coefficient Parameters

After determining the cointegration relationships in the panel model, the Augmented Mean Group (AMG) method was used to estimate the model's long-run coefficients. The AMG estimator, introduced by Eberhardt and Bond (2009), adds a common dynamic effect to the country regression to account for cross-country heterogeneity and cross-sectional dependence. The model can be written as:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \gamma_i \bar{y}_t + \delta_i' \bar{x}_t + \varepsilon_{it} \quad (9)$$

where; y_{it} is the dependent variable, x_{it} is a vector of explanatory variables, $\bar{y}_t = (1/N) \sum_i y_{it}$ and $\bar{x}_t = (1/N) \sum_i x_{it}$ are the cross-sectional averages, ε_{it} is the error term.

The AMG estimator controls for unobserved common factors that may cause cross-sectional dependence by including a common dynamic process obtained from the first-differenced pooled regression (Eberhardt and Bond, 2009);

Estimate the following first-differenced pooled regression with a constant:

$$\Delta y_{it} = \alpha + \Delta x_{it}' \beta + \varepsilon_{it} \quad (10)$$

From this regression, obtain the common dynamic effect, denoted as $\hat{c}_t$. Include this common factor in the country-specific regressions:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \lambda_i \hat{c}_t + \varepsilon_{it} \quad (11)$$

Then the AMG estimator is the mean of the individual slope coefficients:

$$\beta_{AMG} = (1/N) \sum \beta_i \quad (12)$$

The findings regarding the AMG test are presented in Table 9. According to the AMG test results applied to the model, a 1% increase in the CRI variable increased the BANKZ variable, representing banking sector stability, by 1.172%. Similarly, a 1% increase in the GDPG variable resulted in a 0.095% increase in the BANKZ variable. No statistically significant effect of CO2, EFI, and PS variables on the BANKZ variable was found.

Table 9. Estimating Long-run Coefficient Parameters Using AMG Techniques

Variables	Coefficient	Standard Error	p
CRI	1.172	0.486	0.010*
CO2	0.043	0.082	0.596
GDPG	0.095	0.034	0.005*
EFI	-0.006	0.299	0.983
PS	0.287	0.211	0.173
C	-1.405	1.304	0.281
RMSE	0.0464		

4. Conclusion and Recommendations

In today's world, climate change, driven by various factors, has multifaceted impacts. That is why countries are trying to take precautions against climate shocks, increase their resilience, and be prepared economically, governance-wise, and socially. Climate-related shocks have the potential to negatively impact countries' economic growth rates, real economic performance, and the resilience of the financial sector.

The aim of this study is to examine the impact of countries' resilience and adaptation capacity to climate change on banking sector stability. For this purpose, the model, developed for a large panel of 96 countries, was tested using the AMG test, a modern estimator that takes into account heterogeneity and cross-sectional dependence. In this context, examining the impact of climate resilience (or vulnerability) on bank stability using long-term estimators is expected to provide policymakers with a new and distinct perspective.

In this study, the BANKZ was used to represent banking sector stability. The ND-GAIN Country Index was selected to represent climate resilience. Countries with high scores on the index, which ranges from 0 to 100, are less prone to climate change impacts and have lower climate risks. In other words, there is an inverse relationship between a country's ND-GAIN scores and its climate risk level, with a higher ND-GAIN score indicating a lower climate risk level.

Carbon emissions were used as a measure of a country's environmental performance. Furthermore, variables such as economic growth, economic freedom index, political stability, and absence of violence/terrorism were also added to the models. In the model created using these variables (BANKZ, CRI, CO2, GDPG, EFI, PS), the focal independent variable is the CRI, and correlation and VIF tests were performed based on the assumption that there might be a high correlation or multicollinearity problem between the carbon emissions included in the model and the CRI, but since no high correlation or multicollinearity problem was detected, there was no problem in including the two variables in the same model.

Empirical findings indicate that countries' resilience and adaptation capacity to climate change, as measured by the ND-GAIN Country Index, have a positive and significant impact on banking sector stability. This result suggests that banking systems are more robust in countries with lower vulnerability and higher preparedness to the negative effect of climate change. Hence, it can be argued that efforts to reduce countries' vulnerability to the adverse impacts of climate change and strengthen their climate adaptation capacity reduce banks' systemic vulnerabilities by directly and positively impacting their balance sheets, loan portfolios, risk management strategies, reputations, and cash flows. This finding is consistent with a study by Wu et al. (2024), who concluded that countries' exposure to climate risks significantly increases banks' systemic risks. The finding that economic growth improves the financial stability of the banking sector, as evidenced by Demirgüç-Kunt and Detragiache (2011), Kasman and Kasman (2015), Chiaramonte et al. (2016), and Yaseen et al. (2024), demonstrates a relationship between financial stability and macroeconomic performance.

In this regard, it would be beneficial for developed countries to continue to reduce their vulnerability to climate change and strengthen their climate adaptation capacity. Developing countries need to closely follow the policies and strategies of developed countries, seek financial support when necessary, review their risk management approaches, and minimize their technological weaknesses.

In response, banking institutions, in collaboration with regulatory authorities, should develop strategies that limit the potential for climate-related external shocks to trigger sectoral risks. Developed countries can continue to pursue sustainable and inclusive economic growth strategies aimed at enhancing or preserving the financial stability of banks, which hold a significant share of the financial system and are the largest financial intermediaries. Developing countries can improve their strategies in this regard and adopt more environmentally friendly economic policies.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There is no potential conflicts of interest in this study.

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THE ROLE OF FINANCIAL MARKETS IN PREDICTING BIST SUSTAINABILITY INDEX PERFORMANCE: NEW EVIDENCE FROM HYBRID MACHINE LEARNING MODELS

BİST Sürdürülebilirlik Endeksi Performansının Tahmininde Finans Piyasalarının Rolü: Hibrid Makine Öğrenmesi Modellerinden Yeni Kanıtlar

Zeynep ÇOLAK*

Abstract

The increasing importance of sustainable finance makes it critical to understand and accurately model the performance dynamics of investment instruments in this area. This study aims to forecast the return of the BIST Sustainability Index using financial market indicators and to explain the underlying dynamics of this forecasting process, thereby understanding the complex structures of financial markets, investor behavior, and information flow. In this study, eleven different machine learning models were compared with a validation strategy suitable for the time series structure, and the most successful candidates were subjected to hyperparameter optimization. In order to overcome the limitations of single models, a sequential hybrid model based on the Residual Fitting approach was developed. According to the results of the study, the two-stage hybrid model, which uses the Voting Regressor as the main predictor and Random Forest as the error corrector, provided the lowest error (RMSE) and the highest R^2 value. The findings indicate that the BIST_100 index is the most critical determinant, while risk aversion indicators such as Gold, USD, and VIX have a negative effect. This evidence has far-reaching implications for understanding the dynamic relationships between the Sustainability Index and macroeconomic variables.

Keywords:

Sustainable Finance, BIST Sustainability Index, Machine Learning, SHAP, Explainable Artificial Intelligence

JEL Codes:

G19, C53, C58

Öz

Sürdürülebilir finansmanın artan önemi, bu alandaki yatırım araçlarının performans dinamiklerini anlamayı ve doğru bir şekilde modellemeyi kritik hale getirmektedir. Bu çalışma, finansal piyasa göstergelerini kullanarak BIST Sürdürülebilirlik Endeksi'nin getirisini tahmin etmeyi ve bu tahmin sürecinin altında yatan dinamikleri açıklamayı, böylece finansal piyasaların karmaşık yapılarını, yatırımcı davranışlarını ve bilgi akışını anlamayı amaçlamaktadır. Bu çalışmada, zaman serisi yapısına uygun bir doğrulama stratejisi ile on bir farklı makine öğrenimi modeli karşılaştırılmış ve en başarılı adaylar hiperparametre optimizasyonuna tabi tutulmuştur. Tekil modellerin sınırlamalarını aşmak için, Residual Fitting yaklaşımına dayalı sıralı bir hibrit model geliştirilmiştir. Çalışmanın sonuçlarına göre, ana tahminci olarak Voting Regressor ve hata düzeltici olarak Rastgele Orman kullanan iki aşamalı hibrit model, en düşük hata (RMSE) ve en yüksek R^2 değerini sağlamıştır. Bulgular, BIST_100 endeksinin en kritik belirleyici olduğunu, Altın, USD ve VIX gibi riskten kaçınma göstergelerinin ise olumsuz bir etkiye sahip olduğunu göstermektedir.

Anahtar Kelimeler:

Sürdürülebilir Finans, BIST Sürdürülebilir Endeksi, Makine Öğrenimi, SHAP, Açıklanabilir Yapay Zeka

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1. Introduction

In countries where sustainability reports are prepared voluntarily, sustainability indices are seen to significantly encourage businesses to prepare and publish sustainability reports. The most important feature of stock exchanges is that they showcase companies in all their aspects and contribute to the formation of transparent and orderly markets by reinforcing the race for excellence among businesses (Kocamış and Yıldırım, 2016). The distinction between sustainable and non-sustainable businesses, the presentation of this distinction to business stakeholders, and the assessment of sustainability performance have led to the development of the BIST Sustainability Index. This initiative was driven by the need for transparent, sustainable businesses in the market, as well as the recognition that the most effective method for achieving this is through performance measurement using indices.

Companies' performance in these areas is explained through Environmental, Social, and Governance (ESG) factors. ESG is described as a non-financial assessment system that considers the environment, society, and corporate governance to support companies' sustainable development and encourages companies to focus on social interests rather than maximizing their own interests (Chen et al., 2023). The performance of sustainable indices is influenced not only by companies' ESG scores but also by macroeconomic and financial indicators (Friede et al., 2015).

The use of Machine Learning models in the financial sector is rapidly expanding. The vast amount of data generated by the sector while performing its financial intermediation functions also provides a favorable working environment for these models (Şahin, 2024). In machine learning, algorithms have been developed that can process large amounts of nonlinear data in modeling frameworks by establishing complex, advanced neural network structures (Seow, 2025). The majority of these models are inherently complex and lack explanations of the decision-making process, causing these models to be termed as 'Black-Box'. (Quinn, 2023). SHAP (SHapley Additive Explanations) is one such method, and it takes the machine learning model out of the black box, allowing for commentary on the model (Lundberg and Lee, 2017). The SHAP method is an XAI method that focuses on identifying the contribution of features to the output, utilizing the mathematical concept known as the Shapley value in game theory. The Shapley value used in this method represents the average marginal contribution of each feature value among all possible values in the feature space. SHAP can be used for both global and local explanations (Bhattacharya, 2022).

The purpose of this study is to predict the returns of the BIST Sustainability Index and its relationship with financial and macroeconomic variables using machine learning models. The role of the variables behind these predictions is then evaluated and interpreted using SHAP analysis. The original contribution of this study to the literature is the development of a sequential hybrid machine learning model based on the Residual Fit approach to predict the returns of the BIST Sustainability Index and interpretation using SHAP analysis.

2. Conceptual Framework

2.1. The Effect of Macroeconomic Variables on Sustainability Indices

Analyzing the financial performance of sustainability indices, it is equally important to demonstrate the interaction of global and local macroeconomic dynamics on these indices as it is to show the impact of ESG factors.

Drimbetas et al. (2010) investigated the effects of macroeconomic factors on the sustainability index in their study, analyzing the relationship between DJSI data, oil prices, 10-year bond prices, exchange rates, and non-agricultural employment data using monthly data from 1999 to 2008. The GARCH model was used in the study. The study concluded that there is a negative relationship between oil prices and exchange rates, as well as the sustainability index. A positive relationship was found between 10-year bonds and the sustainability index, while no relationship was observed between non-agricultural employment and the sustainability index.

In Sharma et al. (2021), the impact of macroeconomic variables on India's sustainability indices was analyzed. The study found that while there was a relationship between the GREENEX index and crude oil prices, interest rates were not related to the index. Kaur and Chaudary (2022) analyzed the relationship between the sustainable stock market index and macroeconomic variables. The result of the study showed that macroeconomic variables have a long-term equilibrium connection with sustainable stock market prices

Özçim (2022) showed that the oil variable did not affect the volatility of the BIST Sustainability Index, while the exchange rate variable increased it, and the interest rate variable decreased it. Kaya (2023) demonstrated that oil-based fuel prices have a more significant impact on the BIST Sustainability Index than prices for natural gas and coal. Kavas (2025) found a positive relationship between the BIST Sustainability Index and the exchange rate.

2.2. Sustainable Finance and Green Bond

Green bonds are one of the instruments that are used to finance environmentally friendly projects. The proceeds from green bonds help businesses raise capital for environmentally friendly projects and contribute to sustainable development for the future. Issuing green bonds involves certain costs, and investors are reluctant to invest in these bonds due to the perceived risk associated with the projects they finance (Bhutta et al., 2022).

Ehlers and Packer (2017) emphasized that conducive market conditions must be in place for the growing green bonds. Both issuers and investors should be satisfied with the returns and safety of such a security. AlGhazali et al. (2025) examined the relationship between sustainability indices, green bond markets, and oil price shocks. The findings indicate that there is a changing connection between all variables over time.

According to the results of Bařkaya (2025), a positive long-term relationship was found between the BIST100 Index and the BIST Sustainability Index, while a significant negative relationship was found between the BIST100 Index and the S&P Green Bond Index.

2.3. Machine Learning Applications in Sustainable Finance

In recent years, methods such as Interpretable Machine Learning or Explainable Artificial Intelligence have begun to be used in studies related to sustainability in the financial sector. Zhang and Zhao (2026) developed a prediction model for corporate ESG ratings using an XGBoost algorithm enhanced with SHAP interpretability. Siddique and Karim (2025) employed machine learning, deep learning, and ensemble techniques to assess whether ESG and financial indicators can effectively predict carbon risk. Results demonstrate that advanced AI models significantly outperform traditional regressions by capturing complex, non-linear relationships often overlooked by conventional methods. SHAP analysis further identifies environmental disclosure as the most influential predictor. Çankal and Ever (2025) analyzed the relationship between the financial performance of companies listed on the Borsa Istanbul (BIST) Sustainability Index and their renewable energy consumption using the Explainable Artificial Intelligence method.

A review of the literature reveals that there is a lack of studies examining the impact of sustainability indices on macroeconomic variables and financial indicators for emerging markets. This study aims to fill this gap in the literature.

3. Data Set and Methodology

3.1. Data Set and Variables

The dataset used in this study consists of multivariate time series data covering 2015-2025. The data was obtained from Investing.com. The dependent variable of the study, the BIST Sustainability Index, represents companies listed on the Istanbul Stock Exchange that have high ESG scores and strong corporate sustainability performance. The independent variables include financial and macroeconomic indicators that affect the performance of the sustainability index. These variables are the BIST 100 Index, the main index of the Istanbul Stock Exchange; the Turkey 10-Year Bond Yield, an important tool for national economies and monetary policy; the dollar exchange rate, which expresses the value of the US dollar against the local currency; the S&P 500 Index, which consists of the shares of the 500 largest publicly traded companies in the United States and is weighted by market value; the CBOE Volatility Index, which is based on the fundamental principle that trading volumes and stock option pricing are determined by investors; brent crude oil and gold prices.

3.2. Data Preprocessing and Feature Engineering

By their very nature, financial time series often exhibit non-stationarity. This means that the statistical properties of the series, such as mean and variance, change over time, which contradicts the basic assumptions of many econometric and machine learning models (Tsay, 2010). To improve the performance of the models and to approximate the stationarity assumption, all crude price series were transformed into percentage return series. This transformation was done using first-order differencing between the series. After the transformation, the missing data in the first row (NaN) due to the return calculation were removed from the data set.

3.3. Data Set Partitioning and Validation Strategy

In time series data, there is a temporal dependence between observations. Therefore, data partitioning methods based on random shuffling, such as standard cross-validation, run the risk of "data leakage" (Bergmeir and Benítez, 2012), where the model learns from future information to predict the past. This produces misleadingly high accuracy rates that do not reflect the real-world performance of the model.

To avoid this methodological error, the dataset was split without shuffling (shuffle=False), preserving the temporal order. The first 75% of the dataset is used as training data, and the last 25% is used as test data. This fixed-origin validation strategy simulates a realistic forecasting scenario where the model learns only from past data and is tested on future data that it has never seen before.

3.4. Feature Scaling

The majority of the algorithms evaluated in this study are decision tree-based ensemble models (e.g., Random Forest, XGBoost). These models are insensitive to the scale of features as they partition the feature space parallel to the axes, i.e., they are not affected by monotonic transformations of features (Hastie et al., 2009). Therefore, feature scaling (normalization or standardization) is not a prerequisite for these models. In order to maintain methodological consistency and apply a uniform preprocessing pipeline to all models, no further scaling is performed, even for scale-sensitive models such as SVR and MLP Regressor.

3.5. Control and Evaluation of Excessive Learning

Overfitting occurs when a model loses its ability to generalize to new data by memorizing noise and random fluctuations in the training data, primarily due to the model's high variance (Hastie et al., 2009). In this study, the risk of overlearning was managed and assessed in the following ways:

1. **Performance Comparison:** The presence and degree of overlearning were quantitatively determined by comparing the performance of each model on the training set with its performance on the test set. A significant difference between the training and test metrics was considered a strong indicator of overlearning.
2. **Regularization:** Models such as Ridge and Lasso naturally include L2 and L1 regularization mechanisms that penalize coefficients (Tibshirani, 1996). Similarly, algorithms such as Gradient Boosting and XGBoost have regularization parameters that control tree complexity and leaf node values.
3. **Ensemble Methods:** Bagging-based methods, such as Random Forest, reduce variance by averaging over a large number of models (Breiman, 2001). Meta-aggregation methods such as Voting and Stacking aim to produce more robust and generalizable predictions by combining the biases of different model architectures (Wolpert, 1992). In this study, the default hyperparameters of the models are used, which provide a basic level of regularization.

3.6. Descriptive Statistics

Table 1 presents the basic descriptive statistics of the BIST, CBOE VIX, and S&P indices. The findings reveal that the series have different characteristics in terms of their mean levels, the shape of their distributions, and extreme value characteristics.

Table 1. Descriptive Statistics

Variable	Mean	Median	Mx	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
BIST	4062.09	1480.44	15440.06	868.47	4503.75	13.286	0.1420	740.71	0.00
CBOE VIX	18.49	16.70	82.69	09.14	07.36	25.558	124.214	18825.10	0.00
SP	1798.25	1789.35	2406.19	1282.51	263.94	0.0315	-0.8658	79.06	0.00

First of all, the average value of the BIST index was 4062.09, with a low of 868.47 and a high of 15,440.06. The high standard deviation of 4503.75 indicates that the index exhibited significant fluctuations throughout the period. The positive skewness coefficient (1.33) indicates that the distribution is skewed to the right, i.e., high values pull most of the observations upwards. The kurtosis value (0.14) is close to normal, indicating that the extreme value density of the distribution does not increase significantly.

CBOE VIX index results show an average value of 18.49 and a highest observation of 82.69. This indicates that the index can occasionally reach very high levels due to market uncertainties. S&P index results show an average value of 1798.25, ranging between 12. Figure 1 shows the evolution of the BIST SE index over the period 2015-2025.

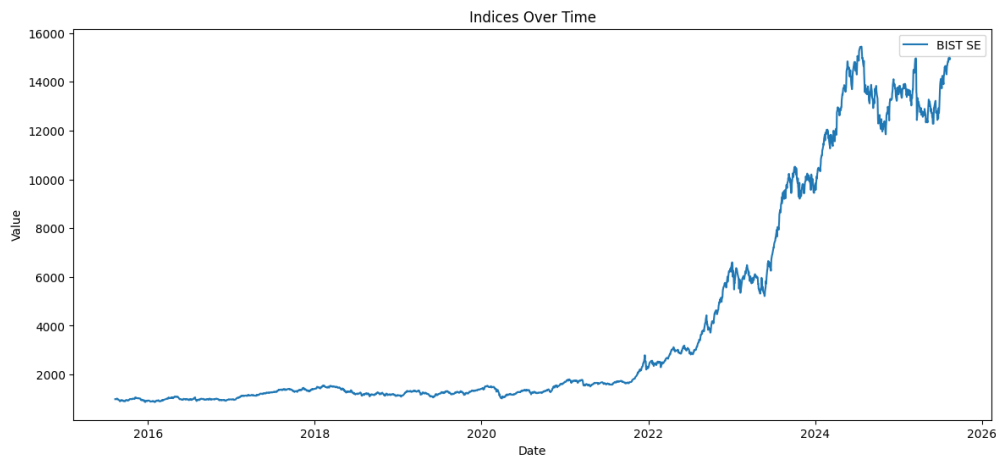


Figure 1. Time Series Dynamics of BIST SE Index

The graph shows that the series remained flat until 2020, then entered a sharp upward trend. Overall, the BIST Sustainability Index demonstrates both growth potential and vulnerability to shocks, in line with the characteristics of emerging financial markets.

4. Methodology

4.1. Voting Regressor

Voting Regressor is a meta-ensemble model that combines the predictions of different machine learning models to produce a final result. The main goal of this approach is to balance the bias or variance that a single model may have by utilizing the collective wisdom of models with different architectures and learning approaches (Dietterich, 2000). Figure 2 shows the schematic architecture of the Voting Regressor model.

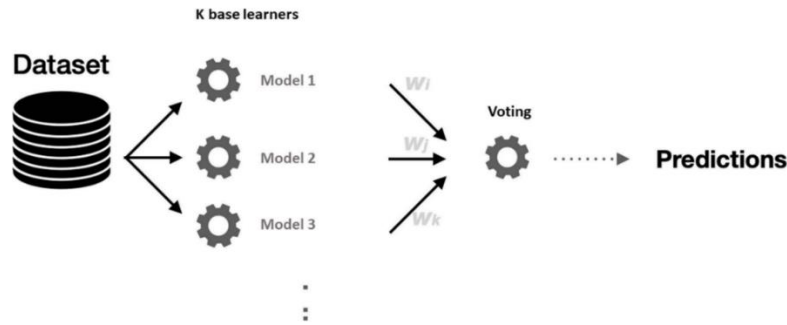


Figure 2. Schematic Architecture of the Voting Regressor Model

As shown schematically in Figure 2, the Voting Regressor architecture starts by presenting the same dataset to multiple independent base learners (K base learners). Each base model (Model 1, Model 2, ...) processes the data according to its own internal learning algorithm and produces an independent prediction (W_i , W_j , ..., W_k). In the final stage, these individual predictions are combined in a voting mechanism. In regression problems, this voting mechanism usually takes a simple or weighted average of all the individual predictions to produce a more robust and usually more accurate final prediction.

In this study, we take advantage of this architecture to integrate the predictions of two structurally different models: (1) a Random Forest optimized to capture nonlinear and complex relationships and (2) a Ridge regression that models more stable and linear relationships through regularization. This diversity allows the models to capture different types of patterns in the data and compensate for each other's weaknesses.

Mathematically, the final estimate ($\hat{y}$) of a Voting Regressor consisting of M base models is expressed as the simple average of the estimate ($h_m(x)$) of each base model, as follows:

$$\hat{y}(x) = \frac{1}{M} \sum_{m=1}^M h_m(x) \quad (1)$$

This simple averaging process softens the effect of extreme outlier predictions of a single model and provides a more stable generalization performance (Hastie et al., 2009).

4.2. Random forest

The Random Forest (RF) algorithm has been extremely successful as a general-purpose classification and regression method (Breiman, 2001). RF is able to handle mixed categorical and numerical features, multiple classes, is insensitive to the scale of features, and has been considered as a powerful supervised learner. $h_m(x)$ m. decision and M total number of trees

Mathematically,

$$f(x) = \frac{1}{M} \sum_{m=1}^M h_m(x) \quad (2)$$

Since each tree in a random forest is trained independently, the error rate is determined by both the accuracy of individual trees and the correlation between trees. Random feature selection reduces correlation and improves model performance.

4.3. Gradient Boosting

Gradient Boosting is an algorithm developed by Friedman (2001) in which each tree is created sequentially, attempting to correct the errors of the previous tree. This method increases the power of the model by focusing on the errors of weak learners. In each iteration, optimization is performed in the direction of the negative gradient to minimize error in line with the trends of the current model. γ_m the learning rate of the m-th tree and $h_m(x)$ the output of the m-th tree.

The mathematical basis of the gradient boosting method is as follows:

$$f_m(x) = f_{m-1}(x) + \gamma_m h_m(x) \quad (3)$$

Gradient boosting adds new trees modeled according to the negative gradient of the loss function and optimizes the model overall. Mathematically, the optimal γ_m value is determined by the update made in the direction of the gradient at each iteration.

4.4. Multilayer Perceptron (MLP)

MLP was developed by Rosenblatt (1958) as a multi-layer version of the perceptron model. Used as a baseline model in financial forecasting, MLP stands out for its ability to model non-linear relationships (Heaton et al., 2016) and can process time series data with its structure consisting of input, hidden, and output layers. Figure 3 shows the basic architecture of a multilayer artificial neural network (MLP).

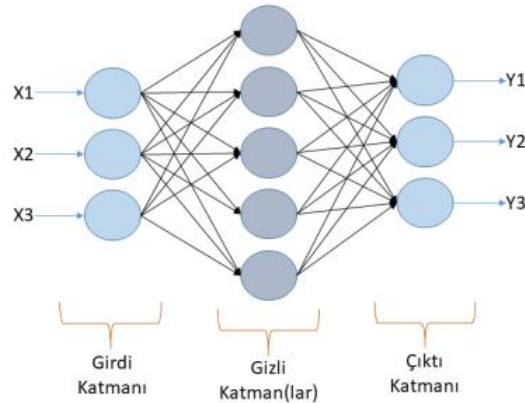


Figure 3. Multilayer Perceptron (MLP)

Haykin (2009) stated that artificial neural networks consist of three basic layers: input layer (X1, X2, X3), hidden layer(s), and output layer (Y1, Y2, Y3) (Haykin, 2009). Rumelhart et al. (1986) demonstrated that hidden layers enhance the network's capacity to learn nonlinear relationships. In this structure, the connections between neurons represent weights, and each layer is fully connected (LeCun et al., 2015). In financial time series, the input layer usually represents historical price and volume data, and the output layer represents the values to be predicted (Heaton et al., 2016).

The flowchart of the methodology of the study is presented in Figure 4.

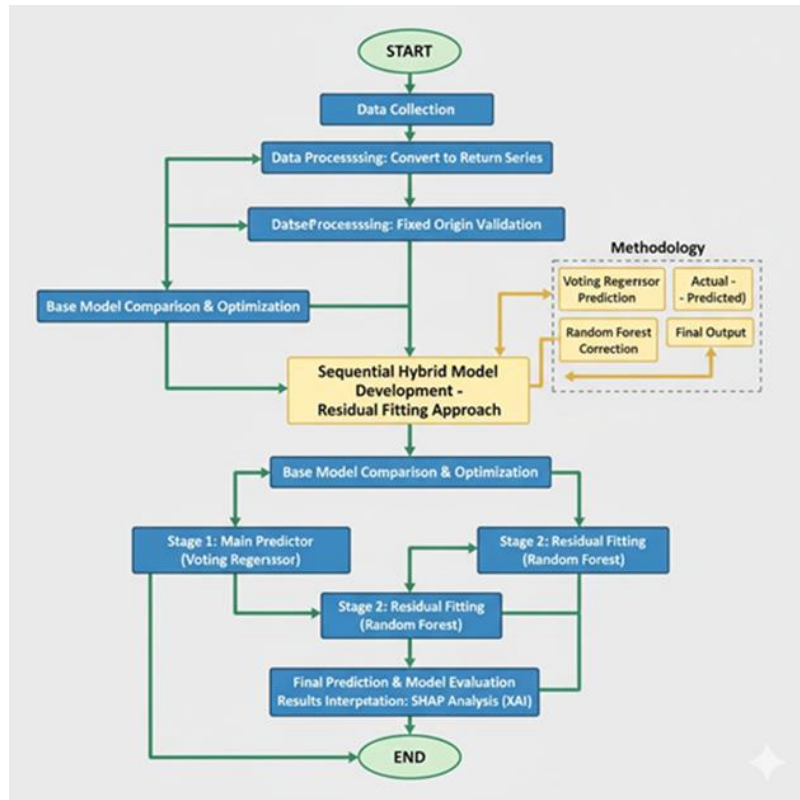


Figure 4. The Flowchart of the Methodology

5. Findings

5.1. Machine Learning Findings

The model results will be tested based on prediction accuracy on test data, the models' generalization capacity, and efficiency. Table 2 presents a comparison of the training and test performance metrics for different machine learning models.

Table 2. Comparison of Training and Testing Performance Metrics of Different Machine Learning Models

Model	Train MAE	Test MAE	Train RMSE	Test RMSE	Train R ²	Test R ²	Time (t)
Voting Regressor	0.6425	0.7522	0.8864	0.9835	0.6964	0.6870	54.647
Random Forest	0.3941	0.7925	0.5461	10.286	0.8848	0.6577	0.7128
Gradient Boosting	0.8840	0.8048	11.787	10.337	0.4632	0.6542	12.494
MLP Regressor	0.9454	0.8319	12.764	10.597	0.3705	0.6367	54.366
CatBoost	0.5282	0.8211	0.6992	10.870	0.8111	0.6177	37.494
Extra Trees	0.0000	0.8469	0.0000	10.990	10.000	0.6092	0.2539
SVR	10.033	0.7429	14.358	11.012	0.2035	0.6076	0.2807
HistGradientBoosting	0.5687	0.8512	0.7791	11.787	0.7655	0.5505	19.934
LightGBM	0.5656	0.8586	0.7762	11.866	0.7672	0.5444	0.9350
XGBoost	0.1747	0.9163	0.2473	12.367	0.9764	0.5051	0.4320
Stacking Regressor	10.742	0.9985	14.950	13.360	0.1365	0.4225	118.219

The table shows that the Voting Regressor model performed best with an RMSE value of 0.9835. This model was successful because combining the predictions of models based on different algorithms yielded a more stable result. The Extra Trees model achieved a perfect result with zero error in the training data. This indicates that the model has completely memorized the training data. Similarly, the XGBoost and Random Forest models show a significant difference between very high training performance and low test performance. This indicates that the models are prone to overfitting. The analysis also reveals that model complexity does not always result in improved performance. The Stacking Regressor, despite being the most complex and having the longest training time, showed the worst performance.

The results of the hyperparameter optimization process will be presented in two stages: the structural configurations of the models (Table 3) and the effects of these configurations on performance (Table 4).

Table 3. Best Hyperparameter Values for the Optimized Models

Model	Best Parameters
Voting Regressor (Opt)	{'ridge__alpha': 10.0, 'rf__n_estimators': 100, 'rf__max_depth': 5}
MLP Regressor (Opt)	{'learning_rate_init': 0.001, 'hidden_layer_sizes': (50,), 'alpha': 0.01, 'activation': 'tanh'}
Gradient Boosting (Opt)	{'subsample': 0.7, 'n_estimators': 100, 'max_depth': 3, 'learning_rate': 0.01}
Random Forest (Opt)	{'n_estimators': 100, 'min_samples_leaf': 2, 'max_features': 'sqrt', 'max_depth': 5}

Table 4. Final Model Performance Metrics after Hyperparameter Optimization

Model	Train RMSE	Test RMSE	Train R ²	Test R ²	Time (s)
Voting Regressor (Opt)	13.434	0.9337	0.8027	0.7179	25.43
MLP Regressor (Opt)	13.993	11.101	0.6435	0.6013	4.60
Gradient Boosting (Opt)	13.996	12.961	0.4832	0.4565	21.44
Random Forest (Opt)	13.707	13.951	0.4541	0.3703	15.47

Table 3 shows that the search algorithm preferred less complex structures for all models. The selected parameters focused on the more general aspects of the models and the fundamental signal in the data. The performance implications of these structural changes are detailed in Table 4, and the findings are best understood in terms of the bias-variance tradeoff. The most obvious success of the optimization is that it effectively eliminates overlearning by reducing the model variance. In all models, the difference between the Training R² and Test R² values is almost completely closed compared to before optimization, proving that the models no longer memorize the training data and can consistently generalize the learned knowledge to the test data. However, reducing model complexity to reduce variance has the potential to increase the model's bias, i.e., the error due to the tendency to simplify the underlying structure of the data.

These results have led to different performances among the models. Random Forest and Gradient Boosting models have been oversimplified to prevent overfitting. This causes a loss in their ability to capture meaningful relationships in the data and a decline in test performance. The Voting Regressor has been found to be the model that best achieves this balance. The highest generalization performance was achieved on the test data with an RMSE of 0.9337 and an R² of 0.7179.

5.2. Hybrid Modeling Strategy: Sequential Residual Fitting

In the hybrid model, two or more models compensate for each other's weaknesses in sequence. The purpose of the secondary model is to predict errors in the primary model (Aslanargun et al., 2007). The stages of the model used in the study are given as follows:

1. Primary Predictor: The Voting Regressor model was selected as the optimized primary predictor.
2. Residual Corrector: The residual values of the Voting Regressor on the training data are calculated.
3. Final Hybrid Forecast: The final forecast for the test data ($\hat{Y}_{\text{hybrid}}$) is obtained by summing the test forecast of the main model and the error forecast of the error-correcting model for the test data:

$$\hat{Y}_{\text{hybrid}} = \hat{Y}_{\text{base}}(\hat{Y}_{\text{test}}) + \hat{Y}_{\text{residual}}(X_{\text{test}}) \quad (4)$$

This approach aims to capture both linear and non-linear patterns more effectively, creating interaction that single models alone cannot achieve. All possible pairwise combinations are tested to determine which model pair produces the strongest empirical interaction. Table 5 shows the role played by the models in the hybrid model architecture.

Table 5. Role of Models in Hybrid Model Architecture

Hybrid Configuration (Main Model -> Error Corrector)	Test RMSE	Test R ²	Test MAE
Voting Regressor -> Random Forest	0.9264	0.7223	0.7299
Voting Regressor -> Gradient Boosting	0.9329	0.7184	0.7305
Gradient Boosting -> Voting Regressor	0.9594	0.7022	0.7623
Voting Regressor -> MLP Regressor	0.9712	0.6948	0.7670
Random Forest -> Voting Regressor	0.9999	0.6765	0.7886
MLP Regressor -> Voting Regressor	10.096	0.6702	0.7459
Gradient Boosting -> MLP Regressor	10.331	0.6547	0.8022
MLP Regressor -> Random Forest	10.384	0.6511	0.7765
MLP Regressor -> Gradient Boosting	10.497	0.6435	0.7815
Random Forest -> MLP Regressor	10.694	0.6300	0.8223
Gradient Boosting -> Random Forest	11.179	0.5956	0.8918
Random Forest -> Gradient Boosting	11.695	0.5574	0.9200

The findings presented in Table 5 reveal the critical impact of the role played by the models in the hybrid model architecture and their interaction on the final performance. According to the results of the analysis, the two-stage hybrid model with Voting Regressor as the main estimator and Random Forest as the error corrector performed the best with a Test RMSE of 0.9264 and a Test R² of 0.7223. This result is even better than the performance of the best single optimized model, Voting Regressor (Test RMSE $\approx$ 0.9337), proving the success of the hybridization strategy.

Since Voting Regressor combines models of different natures (linear and tree-based), it is very good at capturing the main trend and more stable patterns in the data. The Random Forest model, which comes in at the second stage and is skilled at capturing flexible, non-linear relationships, improved the overall prediction by effectively modeling these complex and unsystematic residual values (errors) that Voting Regressor misses. A similar interaction is observed in the second-best combination, Voting Regressor -> Gradient Boosting.

Another important finding in the analysis is the tendency for configurations where the Voting Regressor model is used as the main estimator to be at the top of the table. This shows how important it is for the success of the hybrid model that the forecast made in the first stage is stable and has low variance. When more flexible models such as Random Forest or Gradient Boosting are the main estimators, the residuals (errors) they produce are noisier and chaotic, making it more difficult for the second model to model these errors and leading to lower performance.

Finally, more complex hybrid architectures, such as Stacking, were also tried for this pair, which produced the most successful interaction in this study. However, it was observed that these advanced ensemble learning methods do not yield better results than the more intuitive and interpretable Residual Fitting approach. This suggests that, due to the nature of the problem, direct and sequential correction of each other's errors is more effective than an indirect learning process through a more complex meta-model. In the light of these findings, the Voting Regressor -> Random Forest hybrid model was identified as the final model with the highest performance developed in this research.

5.3. Model Interpretability: SHAP Approach

SHAP is a model-agnostic explanation method that draws its theoretical foundations from the Nobel Prize-winning concept of cooperative game theory and Shapley values (Shapley, 1953). SHAP is one of the explainable artificial intelligence approaches and is used as a powerful machine learning interpretation technique that can measure the absolute impact level of each feature on the predicted outcome and also the direction of this impact.).

SHAP creates an explanation model that expresses the prediction of any machine learning model as a simple sum of the values attributed to each feature:

$$f(x) = \phi_0 + \sum_{i=1}^M \phi_i \quad (5)$$

where $f(x)$ is the model's final prediction for input x ; M is the number of features in the model; ϕ_0 is the base value, which is the average prediction over the entire data set; and ϕ_i is the SHAP value, which indicates the impact of the i -th feature on that prediction. A positive value of ϕ_i indicates that the feature pushes the prediction up from the base value, while a negative value pushes it down.

In this study, we use two basic visualization tools from SHAP to reveal the insights of the best hybrid model (Voting Regressor -> Random Forest):

SHAP Summary Plot: This plot summarizes the impact of each feature on the entire dataset. Each point represents a single prediction for a single feature. The position of the dots on the horizontal axis indicates the SHAP value (impact on the prediction), and the color indicates the value of the feature itself (high or low). In this way, it is globally understandable which features are most important and how the values of these features affect (positively/negatively) the prediction outcome.

SHAP Dependence Plot: This plot shows how the impact of a single feature on the model's output (SHAP value) changes as the value of that feature changes. Furthermore, the color of the dots reflects the value of a second feature that has the strongest interaction with the selected feature, revealing potential interactions between features.

Through these methods, we analyzed not only what the most successful hybrid model predicts, but also which financial indicators influence these predictions, in what direction and to what extent.

6. SHAP Analysis Findings

In this section, the forecasting mechanism of the highest performing Voting Regressor -> Random Forest hybrid model is analyzed using the SHAP (SHapley Additive exPlanations) method. Figure 5 visualizes how important the model assigns to which financial variables and how the values of these variables affect the model's predictions. SHAP Analysis demonstrates that the model goes beyond being merely a black box, linking the nonlinear pattern recognition capabilities provided by machine learning to observable behaviors and market dynamics in financial markets, thereby possessing a meaningful decision-making mechanism. In particular, the relationships captured by the model enrich discussions regarding market inefficiencies, risk-averse behaviors, and the effects of macroeconomic shocks on sustainability indices.

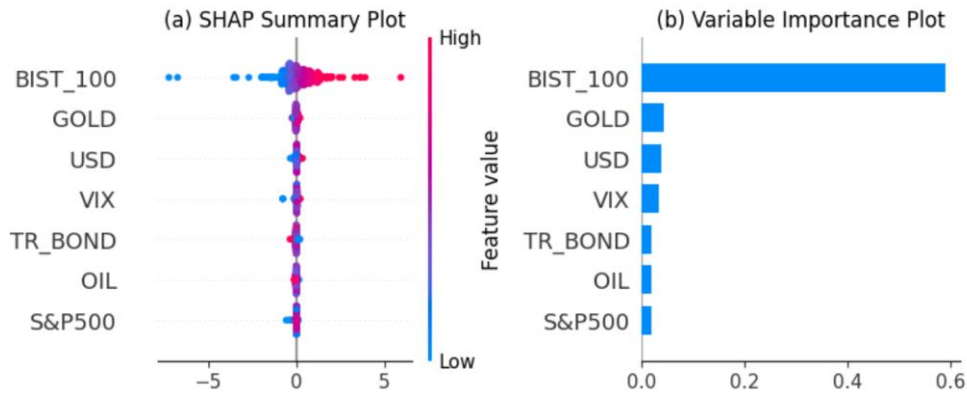


Figure 5. SHAP Summary and Variable Importance Plots for the Best Hybrid Model

The Variable Importance Plot presented in Figure 5(b) shows the average absolute effect that the model attributes to each attribute when making predictions. According to this graph, the return of the BIST_100 index stands out as by far the most critical factor among all other variables. This finding is in line with the basic expectation that the performance of the BIST Sustainability Index is strongly influenced by the main index, which reflects the overall market trend. Following BIST_100, variables such as GOLD (Gold), USD (US Dollar), VIX (Volatility Index), and TR_BOND (Turkish 10-Year Bond) constitute a second level of importance. These variables are macroeconomic and financial indicators that generally reflect the perception of risk, uncertainty, and the search for safe havens.

Figure 5(a) explains the dynamics behind this ranking in more detail. This graph shows the effect of the variable value on the model's output. The fundamental relationships analyzed are as follows:

BIST_100: For this variable, high positive returns are associated with positive SHAP values. This indicates that the model has successfully learned a strong and positive correlation between the two indices.

GOLD and USD: The high values of gold and dollar returns are seen to be associated with negative SHAP values. This situation indicates that investors are avoiding risk by exiting stock markets during periods of uncertainty and turning to safe havens such as gold and foreign exchange.

VIX: The higher values of the fear index negatively affect the model's predictions. This situation is consistent with financial theories that increased market uncertainty fears put pressure on stock returns.

The SHAP analysis shows that the hybrid model fits statistically. This indicates that it has learned relationships that can be interpreted in terms of the fundamental dynamics of financial markets and economic intuition.

6.1. Analysis of Variable Interactions: SHAP Dependency Graphs

SHAP dependency plots show the effect of variables on the model's predictions. These plots are used to show how these effects interact with other variables. Figure 6 shows these interactions for the four most important variables (BIST_100, GOLD, USD, VIX). In these plots, the horizontal axis shows the value of the feature and the vertical axis shows the influence of that feature on the prediction (SHAP value). The color of the dots represents the value of a second variable, automatically determined by the SHAP library, which has the strongest interaction with the main variable.

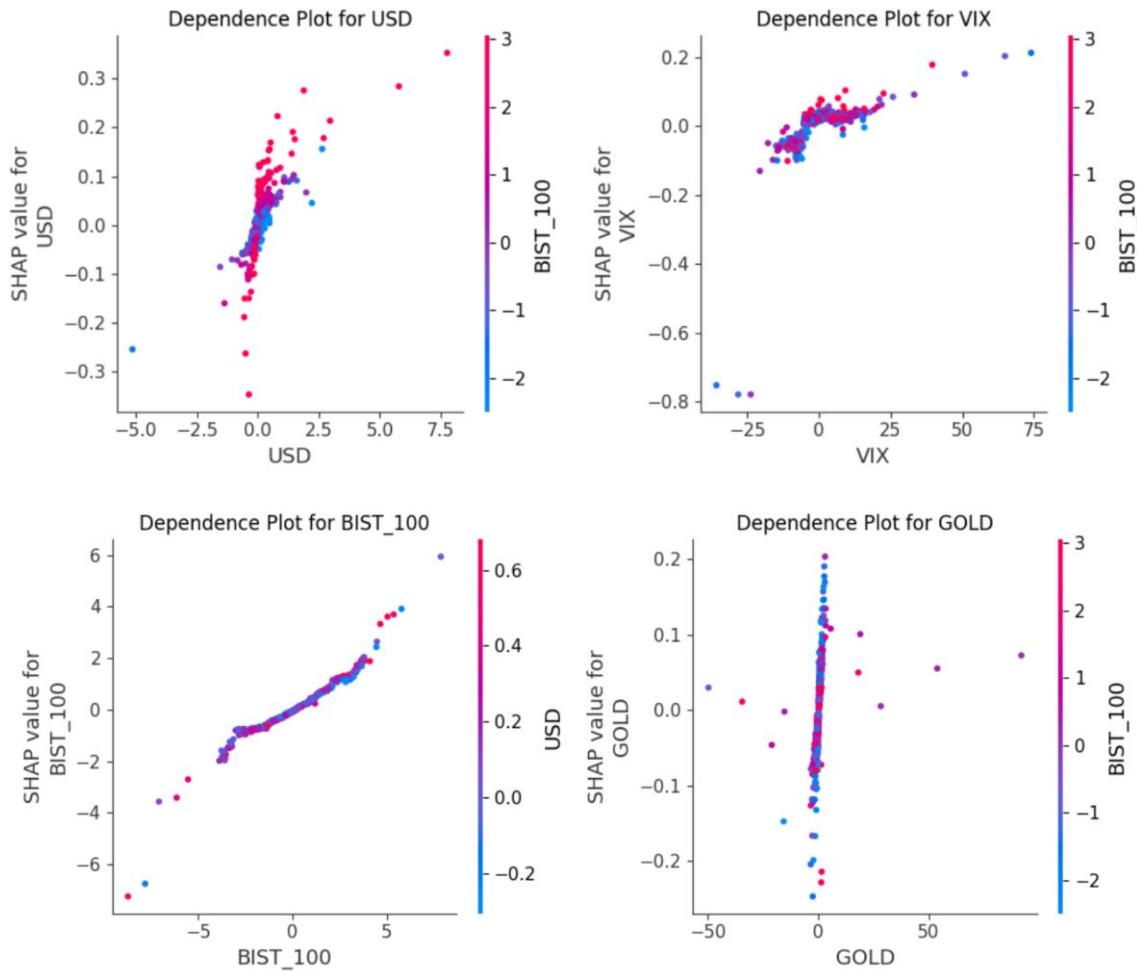


Figure 6. SHAP Dependency and Interaction Plots for the Four Most Important Variables

The graphs in Figure 6 provide important evidence on how successfully the hybrid model learns non-linear and context-sensitive relationships. The BIST_100 graph shows a strong and almost linear positive relationship between the index return and the SHAP value, as expected. According to the SHAP analysis, the factor with the strongest interaction with this variable is USD (Dollar) returns. The color distribution in the chart implies that the positive impact of BIST_100 is more pronounced on days when the USD exchange rate is falling or flat. This suggests that the model has learned that periods when the Turkish Lira appreciates are a more positive signal for the overall market.

The GOLD graph reveals a more complex and noisy relationship structure. Gold returns are concentrated around zero, and SHAP values are also close to zero in this region. However, extreme positive or negative gold returns (dots on the edges of the graph) generally have a negative impact on the model's predictions. This suggests that large price movements in gold are perceived as a signal of uncertainty in the market. According to the color axis, this effect is more pronounced on days when BIST_100 is negative (blue dots), suggesting that the model reinforces the negative relationship between these two variables in risk-off scenarios.

The USD (Dollar) and VIX (Volatility Index) charts exhibit interactions that are highly consistent with financial intuition. Both charts show a positive trend where the SHAP value increases as the value of the variable increases. However, this does not mean that the variables themselves have a positive effect on the Sustainability Index; on the contrary, it should be noted that the SHAP values of these variables are generally below zero.

7. Conclusion

In this study, mean absolute error (MAE), coefficient of determination (R^2), mean square error (MSE), and root mean square error (RMSE) metrics were used to measure the performance of machine learning models. In this study, MAE, R^2 , MSE, and RMSE metrics were used to measure the performance of machine learning models, and the SHAP approach was used to evaluate the importance of explanatory variables.

Model performance was evaluated in three stages. First, an initial screening of eleven different models selected the four models that yielded the best results (Voting Regressor, Random Forest, Gradient Boosting, MLP Regressor). In the second stage, hyperparameter optimization on these four models effectively controlled overfitting. In the final stage, a systematic evaluation of hybrid models based on the Residual Fitting technique was performed. The results show that the Voting Regressor -> Random Forest hybrid model has the best performance with the lowest MAE and RMSE and the highest R^2 value.

The empirical findings reveal that the BIST100 index is at the center of market dynamics. The variable importance ranking shows that BIST100 has a much more substantial impact than all other factors. SHAP analysis results support this finding and show that positive returns in the BIST100 have a positive effect on predictions, while negative returns have a negative effect. The variables with the most significant impact after the BIST100 have been gold, the US dollar, and the volatility index. Vardari et al. (2020) found that the BIST Sustainability Index provided returns to the BIST 100 Index. Kaur and Chaudhary (2022) demonstrated a long-term relationship between the sustainability index and macroeconomic variables. Morales et al. (2019) and Shaikh (2022) showed that increases in the VIX index negatively affect various sustainable investment indices. Özçim (2022) revealed that increases in exchange rates increase the volatility of the BIST Sustainability Index. Therefore, the model's learning that increases in risk indicators such as gold price, exchange rate, and VIX have a negative effect on the sustainability index is similar to the risk-averse behavior observed in the literature. The analysis results of the study show that market risk factors have a strong and guiding effect on sustainability indices. It has been concluded that the hybrid machine learning approach can successfully model these complex relationships.

Policy makers play a critical role in making financial and macroeconomic markets more resilient to fluctuations. To this end, concrete incentive mechanisms should be developed to

increase the corporate resilience of sustainability-focused companies against exchange rate and interest rate shocks. Among these incentives, priority should be given to directly applicable policies such as tax breaks for developing the green bond market, easier access to financial instruments for companies to manage foreign exchange risk, or subsidized loans.

In future research, the model can be tested with different algorithms (e.g., LSTM, XGBoost, CatBoost) and expanded data sets to increase the robustness of the findings. Integration of micro-level ESG scores, company reporting, and news/sensitivity data would strengthen the explanatory power of the model.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement

I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest

There are no potential conflicts of interest in this study.

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CARBON EMISSION INTENSITY AND INVESTMENT EFFICIENCY IN THE EUROPEAN UNION: THE MODERATING ROLE OF ANALYST COVERAGE AND ENVIRONMENTAL INNOVATION

Avrupa Birlięi'nde Karbon Emisyon Yoęunluęu ve Yatırım Etkinlięi: Analist Kapsamı ve Çevresel İnovasyonun Moderatör Rolü

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Abstract

This study examines the impact of carbon emission intensity (CEI) on investment efficiency (IE) as well as the moderating role of analyst coverage and environmental innovation in this relationship for firms operating in the European Union (EU). A panel data set consisting of 5,501 observations of 931 firms for the period 2008-2023 is used. Empirical analyses conducted using the OLS method estimated with Driscoll-Kraay standard errors show that CEI has an overall negative effect on IE, and this effect is particularly pronounced for firms that over-invest. These main findings are robust to alternative investment efficiency measures and alternative estimation methodologies. In addition, analyst coverage and environmental innovation exacerbate the negative effect of CEI on IE. Lastly, heterogeneity analyses indicate that the negative effect of CEI on IE is stronger for firms with lower levels of green revenue and those not participating in the Emissions Trading System (ETS). The study reveals that policies to increase IE should be designed by taking into account firm- and sector-level conditions.

Keywords:

Investment Efficiency, Carbon Emission Intensity, Analyst Coverage, Environmental Innovation, European Union

JEL Codes:

G14, G31, O32, Q52, Q56, Q58.

Öz

Bu çalışma, Avrupa Birlięi'nde (AB) faaliyet gösteren firmalar için karbon emisyon yoęunluęunun (CEI) yatırım etkinlięi (IE) üzerindeki etkisini ve bu iliřkide analist kapsamı ve çevresel inovasyonun moderatör rolünü incelemektedir. 2008-2023 dönemi için 931 řirketin 5.501 gözleminden oluřan bir panel veri seti kullanılmıřtır. Driscoll-Kraay standart hataları ile tahmin edilen OLS yöntemi kullanılarak yapılan ampirik analizler, CEI'nin IE üzerinde genel olarak olumsuz bir etkiye sahip olduęunu ve bu etkinin özellikle aşırı yatırım yapan řirketler için belirgin olduęunu göstermektedir. Bu ana bulgular, alternatif yatırım etkinlięi ölçütleri ve alternatif tahmin metodolojilerine karşı sağlamdır. Ayrıca, analist kapsamı ve çevresel inovasyon, CEI'nın IE üzerindeki olumsuz etkisini daha da arttırmaktadır. Son olarak, heterojenlik analizleri, CEI'nın IE üzerindeki olumsuz etkisinin, yeřil gelir seviyesi daha düşük olan ve Emisyon Ticaret Sistemi'ne (ETS) katılmayan firmalar için daha güçlü olduęunu göstermektedir. Çalışma, IE'yi arttırmaya yönelik politikaların, řirket ve sektör düzeyindeki kořullar dikkate alınarak tasarlanması gerektięini ortaya koymaktadır.

Anahtar Kelimeler:

Yatırım Etkinlięi, Karbon Emisyon Yoęunluęu, Analist Kapsamı, Çevresel İnovasyon, Avrupa Birlięi.

JEL Kodları:

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1. Introduction

Global climate change is currently a major environmental problem, posing a significant threat to the sustainability of economic, social, and ecological systems (IPCC, 2018). A major driver of this threat is greenhouse gas emissions from energy consumption and industrial activities, with carbon dioxide (CO₂) accounting for most of these emissions (Abdallah et al., 2012). Carbon emissions accelerate the global warming process and have detrimental effects on human health, economic stability, and environmental sustainability (Sariannidis et al., 2013). This led the international community to set emission reduction targets through notable international treaties, including the Kyoto Protocol (1997) and the Paris Agreement (2015), which have played a pivotal role in advancing the shift toward a low-carbon economy. This transformation is now seen not only as essential for addressing environmental concerns, but also as a crucial factor in strengthening nations’ economic competitiveness (Scott, 2013).

The European Union (EU) played a pioneering role in this process and introduced the Emissions Trading System (ETS) in 2005 (Action, 2013). ETS has made carbon emissions a direct cost factor for firms. Under this system, firms are given carbon permits within certain emission limits; these permits are either distributed free of charge or auctioned (Ellerman and Joskow, 2008). Furthermore, the European Union (EU) has strengthened its climate agenda by expanding upon the European Green Deal (2019) and the “Fit for 55” legislative package introduced in 2021. Through these frameworks, the EU has established legally binding targets aimed at reducing greenhouse gas emissions by 55% by the year 2030, and reaching full climate neutrality by 2050 (Scheuing and Kamm, 2022; Schlacke et al, 2022). The carbon emissions border adjustment mechanism launched in this context aims to create equal competitive conditions between producers and importers within the EU by preventing carbon leakage (López and Prego, 2019).

In the context of the EU's stringent environmental regulations, carbon emission intensity (hereafter CEI) stands out as a key metric affecting environmental and financial performance (Matsumura et al., 2014). CEI measures the amount of carbon emitted by firms per unit of output, with a high CEI signaling operating inefficiencies and an elevated risk of environmental costs (Bao and Motlagh, 2024). In particular, firms operating in carbon-intensive sectors may experience significant deviations in investment efficiency (hereafter IE) due to high compliance costs arising from the regulatory environment (Kruger et al., 2007). In this context, CEI emerges as a critical environmental and financial risk factor that exacerbates these investment inefficiencies and may adversely affect the short- and long-term financial performance of carbon-intensive firms (Oestreich and Tsiakas, 2024).

The objective of this study is to investigate the impact of CEI on IE using data from 931 firms in the EU for the period 2008-2023. Results show that CEI has a negative effect on IE, which manifests itself in the form of overinvestment. Moreover, we explore the moderating role of analyst coverage and environmental innovation for the CEI-IE relationship and show that the negative effect is more pronounced for firms with higher analyst coverage and higher levels of environmental innovation. To gain deeper insights, we also conduct heterogeneity analyses based on green revenue level, ETS participation, and sector of operation. Our findings indicate that the negative effect of CEI on IE is stronger for firms with lower levels of green revenue and those not participating in the ETS. This effect is statistically significant, particularly within the basic materials, consumer cyclical, consumer non-cyclical, and technology sectors, whereas a positive association is observed in the utilities sector.

This study contributes to the literature on several fronts. First, it extends classical IE models by incorporating CEI as a determinant of IE. While prior studies linked CEI to firm-level outcomes such as profitability (Ganda and Milondzo, 2018; Desai et al., 2022), market capitalization (Hardiyansah et al., 2021), and capital structure (Liu et al., 2021), none have directly examined its impact on IE in the EU. The few studies addressing the CEI-IE relationship rely on limited single-country samples, such as those focused on China (Chen et al., 2022; Wang and Zhang, 2024). Hence, we address this gap by analyzing the CEI-IE relationship with a multi-country dataset of EU firms, using agency theory, information asymmetry theory, the resource-based view, and the Porter hypothesis as our main theoretical perspectives. The EU provides a particularly relevant setting as member states are subject to some of the world's most strict environmental regulations and advanced carbon market practices such as the ETS. These policies raise compliance costs, heighten uncertainty, and increase financing constraints for high-CIE firms (Venmans, 2016; Hintermayer, 2020; Hui and Oh, 2021; Zhang et al., 2019).

Second, this study investigates how institutional and market-based mechanisms, namely analyst coverage and environmental innovation, moderate the CEI-IE relationship. Prior literature suggests that external control mechanisms, such as analyst coverage, can improve investment decisions by reducing information asymmetry and monitoring managers. However, it is not clear how these mechanisms work in high-CEI contexts, as intensified monitoring may create short-term performance pressures. Likewise, environmental innovation, viewed through the resource-based perspective as a strategic capability and through the Porter hypothesis as a regulatory response, can reduce the inefficiency caused by CEI. Yet, in practice, symbolic strategies such as greenwashing may reduce these benefits. By analyzing these moderators together, our study adds to the understanding of how institutional and market-based mechanisms shape the CEI-IE relationship.

Finally, we extend the literature by examining how the CEI-IE relationship varies across firm-level characteristics, specifically green revenue shares, ETS participation, and sector of operation, which have received limited attention in prior studies. Overall, our contributions not only advance theoretical debates on the determinants of IE but also provide policy-relevant insights into how carbon intensity interacts with market monitoring, innovation, and firm heterogeneity in the highly regulated EU setting.

The structure of the paper is as follows. The subsequent section presents a literature review and formulates the research hypotheses. The methodology section outlines the data sources, defines the variables employed in the analysis, and explains the empirical strategy. The findings are then discussed in the results section. Finally, the paper ends with a summary of the key outcomes and their broader implications.

2. Literature Review and Hypothesis Development

2.1. Carbon Emission Intensity and Investment Efficiency

IE is a key indicator that reveals the extent to which firms can correctly evaluate available investment opportunities and use capital efficiently (Stein, 2003). According to neoclassical investment theory and Modigliani and Miller (1958), firms should invest in initiatives that offer positive net returns and aim to attain the most efficient investment level, where the marginal return is balanced by the marginal cost. However, in reality, firms often deviate from this optimal level,

resulting in inefficiencies such as overinvestment in low-return projects or underinvestment in profitable ones (Biddle et al., 2009).

CEI, which refers to a firm's carbon emissions per unit of revenue or output and is considered a key indicator of sustainability performance. Firms with high carbon intensity face operational risks due to increased regulatory obligations, compliance costs, carbon pricing, and public pressure (Dobler et al., 2014; Qi et al., 2022). These risks create uncertainty in the investment environment, which may influence how firms allocate their capital. Accordingly, the impact of CEI on IE can be investigated through several theoretical perspectives, most notably agency theory, information asymmetry theory, the resource-based view, and the Porter hypothesis.

From an agency theory perspective (Jensen and Meckling, 1976), CEI may impair IE. In this framework, high carbon emissions can be considered a reflection of managerial opportunism, where managers exploit free cash flows to invest in polluting sectors despite their long-run costs. This form of “empire-building” negatively impacts IE since resources that could have been used in value-maximizing projects are diverted to environmentally harmful and low-return investments. By prioritizing personal interests over shareholder value maximization, managers reduce the efficiency of investment decisions.

Similarly, information asymmetry theory (Myers and Majluf, 1984) suggests that firms with high CEI face greater uncertainty about future penalties, reputational risk, or market responses. This widens the information gap between managers and investors, increasing the firm's perceived risk and thereby raising the cost of capital (Gulen and Ion, 2016). This often results in underinvestment in profitable projects due to financing constraints or overinvestment in symbolic activities (e.g., “greenwashing”) to signal environmental commitment (Lyon and Maxwell, 2011; Souguir et al., 2024). Both of these outcomes reduce efficiency.

From a resource-based view (Barney, 1991), carbon emissions reflect whether a firm has the necessary resources and capabilities, such as clean technologies, to cope with environmental challenges. Firms that are successful in lowering carbon emissions gain strategic advantages that may improve their IE. On the other hand, firms with high CEI are tied to rigid carbon-intensive production processes, leading to inefficient investment decisions.

Finally, the Porter hypothesis argues that carefully structured environmental policies have the potential to enhance not only ecological outcomes but also firms' financial performance, primarily by stimulating innovation within organizations (Porter and van der Linde, 1995). When firms are forced to decrease their carbon emissions, they often redesign production processes with cleaner and more efficient technologies. These innovations can lower long-term costs, improve competitiveness, and ultimately increase IE. Accordingly, firms with CEI are less likely to benefit from these innovations, resulting in investment inefficiencies.

Overall, the theoretical perspectives discussed above suggest that high CEI may reduce IE by amplifying agency problems, widening information gaps, constraining resources and capabilities, and limiting the innovation benefits of environmental regulation. Building on these mechanisms, empirical studies investigated the effect of carbon emissions on several firm-level outcomes. Studies in various countries and sectors show that carbon emissions and carbon intensity generally negatively affect firm value and financial performance (Lee et al., 2015; Laskar et al., 2022; Miah et al., 2021; Nguyen, 2018; Ferrat, 2021). Recent studies show that

carbon-related risks and regulatory structures can significantly affect firms' investment decisions and efficiency. For example, Chen et al. (2022) show that the carbon emission trading system introduced in China increases firm IE by limiting excessive investment. Similarly, Wang and Zhang (2024) find that the pilot ETS implementation in China reduces investment inefficiency, especially for firms with high innovation capacity and institutional investor ownership. On the other hand, there are also studies focusing on voluntary carbon verification and disclosure mechanisms. Luo and Pan (2025) argue that carbon verification reduces underinvestment and improves the information environment in an international sample of CDP (formerly referred to as the Carbon Disclosure Project) participating firms, while Luo et al. (2025) argue that carbon risk negatively affects labor IE, especially for high-polluting and financially constrained firms.

Drawing upon the earlier discussed theoretical and empirical insights, the initial hypothesis of this research is formulated as follows.

H₁: CEI has a negative impact on IE for firms operating in EU.

2.2. Carbon Emission Intensity, Analyst Coverage, and Investment Efficiency

As discussed earlier, information asymmetry theory suggests that investors' lack of reliable information about the firm's environmental risks may distort capital allocation and negatively affect IE (Myers and Majluf, 1984). In this context, analysts function as external information intermediaries, providing regular information to the market by monitoring firms' financial and environmental performance (Schipper, 1991; Knyazeva, 2007). Broader analyst coverage forces firms to disclose more detailed, timely, and transparent information on their environmental risks, enabling investors to make informed decisions (Irani and Karamanou, 2024; Cheng et al., 2025). In line with that, Liu (2024) finds that broader analyst coverage contributes positively to firms' environmental investment behavior, enhances the transparency and reliability of ESG disclosures, and strengthens managerial accountability regarding environmental outcomes. Similarly, Downar et al. (2021) show that firms with increased analyst coverage after mandatory environmental regulations reduce carbon emissions more.

Beyond information provision, analysts also play a monitoring role by exerting pressure on managers for transparency and accountability (Zheng and Shen, 2024). From an agency theory perspective (Jensen and Meckling, 1976), such monitoring can limit opportunistic behavior and reduce the tendency of managers to overinvest in polluting projects.

However, the effect of analyst coverage is not always positive. Some studies emphasize that analyst pressures may lead firm management to prioritize immediate financial goals at the expense of environmental projects with long-term payoffs (Chan and Hameed, 2006; Chun and Shin, 2018); He and Tian, 2013; Guo et al., 2019). Similarly, Qian et al. (2019) show that under analyst pressure, managers tend to prioritize short-term projects with quick returns, ignoring long-term environmental issues such as carbon emission intensity. This may lead to strategic deviations that may further reduce IE in firms with high carbon emission intensity. Indeed, Zhang et al. (2023) emphasize the strategic steering power of analysts that may lead to deviations from sectoral norms.

In sum, an increase in analyst coverage can help discipline managers by reducing information asymmetry and help investors assess environmental risks more accurately. However, at the same time, it may increase market pressure by making environmental risks such as carbon

emission intensity more visible, which may lead managers to postpone long-term environmental investments or avoid risky projects altogether. In this framework, analyst coverage may play both a supportive and a restraining role on IE. Accordingly, hypothesis H₂ is formulated to capture both the negative and positive effects of analyst coverage on CIE-IE relationship.

H₂: Analyst coverage has a moderating role on the negative relationship between CEI and IE.

2.3. Carbon Emission Intensity, Environmental Innovation, and Investment Efficiency

Environmental innovation involves creating or substantially enhancing products, processes, organizational models, or systems with the objective of minimizing or removing their environmental footprint (Popp et al., 2010; Kemp and Arundel 1998). Such innovations can provide both environmental and economic benefits by reducing environmental pollution and resource use and are considered a valuable tool for firms to achieve their sustainable development goals (Rennings, 2000). In their analysis of Chinese data, Zhang et al. (2017) show that environmental innovation is particularly effective in reducing carbon emissions through energy efficiency, knowledge-based innovation, and resource utilization. Similarly, Popp et al. (2010) emphasize that the impact of environmental innovation becomes stronger when these technologies are widespread and effectively implemented.

Beyond improving environmental outcomes, environmental innovation also influences firms' IE. Firms that engage in such innovation typically disclose their environmental strategies, performance indicators, and technological improvements in greater detail. This increased corporate transparency reduces information asymmetries between managers and investors, leading to more efficient investments (Rehman et al., 2024). Moreover, environmental innovation enables firms to respond strategically to regulatory requirements and stakeholder expectations, improving both environmental and financial performance (Yu et al., 2017).

From a resource-based view perspective (Barney, 1991), environmental innovation represents a unique and inimitable capability that enhances competitiveness, reduces operational costs, and strengthens reputation (Andries and Stephan, 2019). Similarly, the Porter Hypothesis (Porter and van der Linde, 1995) argues that well-designed environmental regulations encourage firms to innovate. Such innovations not only improve ecological outcomes but also make firm more competitive and strengthen IE (Xing et al., 2024). In this sense, firms that successfully adopt environmental innovations are more likely to reduce the inefficiency risks associated with high CEI.

However, a growing number of recent studies show that the positive effects of environmental innovation on IE are not always realized in practice. While genuine innovations improve IE, some high-CEI firms may substitute real innovation with symbolic practices such as greenwashing (Li et al., 2023; Hawn and Ioannou, 2016). These practices create the illusion of environmental innovation, without delivering real environmental and financial benefits, thereby weakening the effectiveness of environmental innovation as a mechanism for improving IE (Delmas and Burbano, 2011; Zahid et al., 2023). This problem is particularly prevalent among firms that are motivated to achieve high ESG scores without real operational transformation (Chen et al., 2021; Laufer, 2003).

The above discussion suggests that environmental innovation may weaken or strengthen the relationship between CEI and IE depending on the circumstances. While genuine innovation may mitigate the negative impact of CEI on IE, symbolic actions may mask underlying inefficiencies or even exacerbate them. Accordingly, we propose the following hypothesis.

H₃: Environmental innovation has a moderating role on the negative relationship between CEI and IE.

3. Methodology

3.1. Data and Sample

The dataset employed in this study comprises 931 publicly listed, non-financial firms operating within EU member countries over the 2008–2023 period. Information on CO₂-equivalent emissions, financial metrics, analyst following, and environmental innovation is retrieved from the London Stock Exchange Group (LSEG) database. After eliminating records with missing values, 5,501 firm-year observations remain for empirical analysis. To minimize the influence of extreme values on the results, all variables are winsorized at the 1st and 99th percentiles. Given that the number of observations varies across years, the dataset forms an unbalanced panel. All statistical procedures are performed using Stata 17. Table 1 Panel A displays the distribution of observations by country, while Table 1 Panel B shows the sectoral breakdown, including both percentage and cumulative shares.

Table 1. Country-Level and Sectoral Distribution of Observations

Panel A. Country-Level Distribution of Observations*

Country of Headquarters	Number of Observation	Number of Firm	Percent (%)
Austria	184	29	3.34
Belgium	230	41	4.18
Denmark	307	48	5.58
Finland	373	58	6.78
France	1003	138	18.23
Germany	1041	189	18.92
Greece	98	20	1.78
Ireland; Republic of	245	33	4.45
Italy	101	21	1.84
Luxembourg	153	29	2.78
Netherlands	283	43	5.14
Other*	74	21	1.35
Poland	145	26	2.64
Portugal	73	11	1.33
Spain	210	33	3.82
Sweden	981	191	17.83
Total	5501	931	100.00

Table 1 Continued

Panel B. Sectoral Distribution of Observations

Economic Sector Name (Classified by LSEG Database)	Number of Observation	Percent (%)	Cumulative (%)
Basic Materials	754	13.71	13.71
Consumer Cyclical	963	17.51	31.21
Consumer Non-Cyclical	405	7.36	38.57
Energy	258	4.69	43.26
Healthcare	489	8.89	52.15
Industrials	1,318	23.96	76.11
Real Estate	343	6.24	82.35
Technology	862	15.67	98.02
Utilities	109	1.98	100
Total	5,501	100	

* Countries with observation counts below 1% are not included in the table. These countries are Cyprus, the Czech Republic, Hungary, Lithuania, Malta, Romania, and Slovenia.

3.2. Variables

3.2.1. Dependent Variable

The dependent variable of the study is IE, a key financial performance indicator that reflects how efficiently firms utilize existing investment opportunities. The indirect approach, suggested by Biddle et al. (2009) and widely adopted in the literature, was used as the measurement method. In the first stage, the expected investment level for each firm in the following period (t+1) is estimated with the following panel data model using the Sales Growth variable (Equation 1):

$$Investment_{i,t+1} = \alpha + \beta_1.SalesGrowth_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

Investment_{t+1} represents the total investment rate of the firm in period t+1. This rate is calculated as the sum of capital expenditures, R&D expenses, and merger and acquisition costs, minus cash inflows from the sale of fixed assets in the relevant year. The net investment amount is normalized by total assets from the previous year and expressed as a percentage. Sales Growth is calculated as the rate of change in the firm's income from year t-2 to year t-1. In the process of estimating the investment model, separate cross-sectional regressions were applied for each year and each sector. In the sectoral classification, the TRBC Industry Group Name in the LSEG database was used as the basis. This approach provides a more accurate and comparable measurement of IE by controlling the effect of structural differences between sectors.

In the second stage, the difference between expected and actual investment is calculated for each firm-year observation as the residual (ε). Following McNichols and Stubben (2008), the absolute values of the residuals are taken and multiplied by -1 to construct the IE variable. The resulting measure is presented in Equation (2).

$$IE_{i,t+1} = -|\varepsilon_{i,t+1}| \quad (2)$$

In this method, a low absolute value of the deviation indicates that a firm's investment decisions are close to the expected level, reflecting high IE. That is, the firm allocates its capital optimally and avoids excessive or inefficient investment behavior. Conversely, a higher deviation reflects investment inefficiency, arising from suboptimal decisions such as overinvestment or underinvestment. Positive residuals indicate overinvestment, while negative residuals indicate

underinvestment. This methodology allows both types of inefficiency to be captured within a single indicator, enabling a comparative and objective assessment of firms' IE.

3.2.2. Independent Variables

CEI is a variable expressed as the amount of CO₂ equivalent emitted per unit of output or activity and is considered a key indicator for assessing environmental performance and climate-related risks (Shah, 2024). In this context, Scope 1 emissions refer to greenhouse gases that are directly released from sources that are owned or controlled by the organization itself (e.g., on-site fuel use and company vehicles). These emissions, which are easier to monitor and report, are an essential element of the corporate carbon footprint. In contrast, Scope 2 emissions refer to indirect greenhouse gas emissions that result from the generation of purchased energy, such as electricity, steam, heat, or cooling consumed by the company to meet its operational requirements (Mytton, 2020; Hertwich and Wood, 2018).

CEI is measured by taking the natural log of the total emissions from both Scope 1 and Scope 2 sources (sourced from the LSEG database) to net sales revenue. This method provides a comparable and literature-consistent indicator of carbon emission intensity by reducing the effect of differences in firm size and volume of activity (Choi and Luo, 2021; Perdichizzi, 2024).

3.2.3. Moderator Variables

The moderator variables of the study are analyst coverage and environmental innovation. Analyst coverage was measured in line with To et al. (2018), and it is quantified by counting the distinct analysts providing profit projections for the company during the year leading up to the fiscal year-end. To enhance statistical validity, the raw value is log-transformed. This transformation yields the first moderator variable, AnalystCoverage. This variable represents the external monitoring role of analysts on the firm, and its effects on investment decisions are evaluated through the interaction term in the analyses.

Following prior studies (e.g., Rehman et al., 2024; Zaman et al., 2021), the second moderating variable, Environmental Innovation, is measured using the “environmental innovation score” obtained from the LSEG database. This score reflects a firm's capacity to create new market opportunities through environmentally friendly products and processes while reducing environmental costs. The score is based on a composite index of 20 quality dimensions adjusted for sectoral differences and ranges from 0 to 100, with higher scores indicating that the company attaches great importance to environmental innovation (Rehman et al., 2024).

3.2.4. Control Variables

Drawing on prior literature (e.g., Chen et al., 2022; Liu et al., 2024; Luo et al., 2025), this study incorporates a set of firm-specific control variables to better identify the influence of CEI on IE. These variables not only increase comparability with previous literature but also aim to isolate the causal relationship more accurately by reducing the biases that may be caused by the omitted correlated variables in the model.

In particular, the model includes Tobin’s Q, firm size, asset tangibility, financial slack, firm age, and leverage as control variables to account for firm-specific characteristics. Detailed definitions and measurement approaches for these variables are provided in Table 2.

Table 2. Variable Definitions and Calculations

Variable	Symbol of Variables	Definition
Investment Efficiency	IE	Following Biddle et al. (2009), and as described in Section 3.2.1 Dependent Variable, it is computed as the negative of the absolute residuals from Equation (1), where higher values indicate greater efficiency.
Carbon Emission Intensity	CEI	is determined by applying the natural log to the sum of Scope 1 and Scope 2 CO ₂ emissions divided by net sales revenue.
Analyst Coverage		is defined as the natural logarithm of the number of distinct analysts providing earnings forecasts for the firm.
Environmental Innovation		is measured using the environmental innovation score retrieved from the LSEG database, capturing a firm's commitment to environmental innovation.
Firm Value	TOBIN	is calculated by dividing the firm’s market capitalization and total assets (after subtracting book equity) by total assets.
Firm Size	SIZE	is measured as the natural logarithm of total assets.
Firm Asset Structure	TANG	is defined as the ratio of net PPE to total assets.
Financial Slack	FINSLACK	is computed as the natural logarithm of the number of years since incorporation, calculated as $\ln(\text{Fiscal Year} - \text{Year of Incorporation} + 1)$.
Firm Age	AGE	is measured as the natural logarithm of the number of years since incorporation, calculated as $\ln(\text{Fiscal Year} - \text{Year of Incorporation} + 1)$.
Firm Leverage	LEV	is measured as the proportion of current liabilities relative to total assets.
Green Revenue Dummy		is a binary indicator equal to 1 if a firm’s total green revenue surpasses the sample mean (11.6 billion), and 0 otherwise.
ETS Dummy		is a dummy variable coded as 1 if the firm is included in an ETS, and 0 if it is not.

3.3. Model Design

To empirically investigate the impact of carbon emission intensity on firm-level IE, the following baseline panel regression model is employed:

$$IE_{i,t+1} = \alpha_0 + \beta_1 CEI_{i,t} + \sum \beta_j Controls_{j,i,t} + Year\ FE + Industry\ FE + Country\ FE + \varepsilon_{i,t+1} \quad (3)$$

where i denotes the firm and t denotes the year. The dependent variable $IE_{i,t+1}$ indicates the IE of firm i in year $t+1$. The key explanatory variable, $CEI_{i,t}$, captures the firm’s environmental performance and is constructed by taking the natural logarithm of the combined Scope 1 and Scope 2 carbon emissions (sourced from the LSEG database), scaled by net sales revenue. This variable reflects the amount of carbon emitted per unit of revenue, serving as a proxy for firm-level environmental risk exposure. To control for other firm-specific characteristics that may influence IE, the model includes a vector of control variables ($Controls_{j,i,t}$), such as Tobin Q, firm

size, asset tangibility, financial slack, firm age, and leverage (detailed in the Section 3.2.4 and Table 2). The error term $\varepsilon_{i,t+1}$ captures unobserved firm-level shocks and omitted variables that may affect IE. The coefficient β_1 quantifies the extent to which carbon emission intensity is associated with deviations from optimal investment behavior.

In line with standard empirical practice, all explanatory variables are lagged by one period to reduce the risk of reverse causality. Furthermore, to control unobserved differences that may affect IE, the model includes fixed effects for year (Year FE), industry (Industry FE) based on the LSEG TRBC Industry Group Name classification, and country fixed effects (Country FE). These fixed effects help account for time-specific shocks, sectoral characteristics, and country-level institutional differences. The regression is estimated using Ordinary Least Squares (OLS) with Driscoll-Kraay standard errors, which are robust to heteroskedasticity, autocorrelation, and cross-sectional dependence (Driscoll and Kraay, 1998).

Additionally, the study constructs Equation (4) to examine the moderating role of analyst coverage in the relationship between CEI and IE:

$$IE_{i,t+1} = \alpha_0 + \beta_1 CEI_{i,t} + \beta_2 AnalystCoverage_{i,t} + \beta_3 (CEI_{i,t} \times AnalystCoverage_{i,t}) + \sum \beta_j Controls_{j,i,t} + Year\ FE + Industry\ FE + Country\ FE + \varepsilon_{i,t+1} \quad (4)$$

This specification extends Equation (3) by incorporating two additional terms: $AnalystCoverage_{i,t}$ which reflects the level of external monitoring by analysts for firm i , and the interaction term $(CEI_{i,t} \times AnalystCoverage_{i,t})$, which captures the moderating effect of analyst coverage on the relationship between CEI and IE. The coefficient β_3 indicates whether analyst coverage mitigates or amplifies the effect of CEI on IE.

Lastly the study constructs Equation (5) to examine the moderating role of environmental innovation in the relationship between CEI and IE:

$$IE_{i,t+1} = \alpha_0 + \beta_1 CEI_{i,t} + \beta_2 EnvironmentalInnovation_{i,t} + \beta_3 (CEI_{i,t} \times EnvironmentalInnovation_{i,t}) + \sum \beta_j Controls_{j,i,t} + Year\ FE + Industry\ FE + Country\ FE + \varepsilon_{i,t+1} \quad (5)$$

This specification extends Equation (3) by incorporating two additional terms: $Environmental\ Innovation_{i,t}$, which reflects the firm's efforts toward developing or adopting environmentally sustainable technologies, and the interaction term $CEI_{i,t} \times EnvInnovation_{i,t}$, which captures the moderating effect of environmental innovation on the relationship between CEI and IE. The coefficient β_3 indicates whether environmental innovation attenuates or reinforces the impact of CEI on IE.

4. Results

4.1. Descriptive statistics

The descriptive statistics of the main variables used in the analysis are presented in Table 3. The average value of IE is -4.874, with a median of -3.130, indicating significant deviations from optimal investment levels across the sample firms. When broken down into components, the

mean of under-investment is -3.884, whereas the mean of over-investment is 6.536. These figures suggest that under-investment is more prevalent than over-investment in the sample, which may be attributable to market frictions and constraints in accessing external financing (Chen et al., 2011). The CEI variable has an average of -10.364, reflecting considerable variation in environmental performance among firms. The mean value of AnalystCoverage is 2.292, suggesting that, on average, listed firms in the sample are followed by approximately 9 analysts per year.

Table 3. Descriptive Statistics

Variable	Observation	Means	Std. dev.	Min	Median	Max
IE	5501	-4.874	6.135	-53.195	-3.130	-0.076
Under Invest	3343	-3.884	3.508	-26.246	-2.875	-0.076
Over Invest	2158	6.536	9.428	.0002	3.627	90.033
CEI	5501	-10.364	1.903	-14.996	-10.488	-5.594
AnalystCoverage	5324	2.292	0.897	0.000	2.485	3.891
EnvironmentalInnovation	5500	41.095	32.267	0.000	32.000	98.407
TOBIN	5501	1.828	1.643	0.406	1.333	30.424
SIZE	5501	22.239	1.567	16.566	22.298	24.949
TANG	5501	0.243	0.194	0.000	0.200	0.945
FINSLACK	5501	0.116	0.099	0.000	0.090	0.938
AGE	5501	3.286	0.934	0.000	3.332	5.142
LEV	5501	0.265	0.149	0.000	0.257	0.868

4.2. Baseline estimations

Presented here are the main estimation results analyzing how CEI affects IE. The estimations are performed using the ordinary least squares (OLS) method and Driscoll-Kraay standard errors, and the results are reported in Table 4.

Table 4. The Effect of Carbon Emission Intensity on Investment Efficiency

Variables	Baseline Model	Under-Investment	Over- Investment
CEI	-0.165*** (-4.33)	0.008 (0.34)	-0.411*** (-3.11)
TOBIN	-0.384*** (-6.18)	0.221* (1.86)	-0.440*** (-3.39)
SIZE	0.304*** (6.10)	0.024 (1.03)	0.605*** (8.10)
TANG	0.738 (0.98)	2.697*** (10.87)	1.687 (1.14)
FINSLACK	-2.356 (-1.67)	0.971* (1.97)	-8.228** (-2.96)
AGE	0.385*** (5.42)	0.074* (2.06)	0.723*** (3.18)
LEV	-1.244* (-1.86)	-1.585*** (-4.65)	-2.245* (-1.82)
Constant	-12.707*** (-13.64)	-4.421*** (-5.44)	-23.061*** (-9.71)
F - value	302.7***	296.1***	125.9***
R-squared	0.144	0.277	0.173
Observations	5501	3343	2158
Number of firms	931	772	647

Note: t-statistics are reported in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10. All estimations include fixed effects for year, industry, and country.

4.3. Robustness Checks

To test the methodological robustness of our main findings, additional estimates were performed using the System GMM approach, which accounts for potential endogeneity and dynamic endogeneity issues (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). To ensure robustness against standard error deviations in the estimates, the proposed corrections for two-stage GMM were followed (Windmeijer, 2005). According to the results presented in Table 5, the lagged dependent variable (L.IE) is positive and statistically significant across all model specifications. The coefficient of CEI is negative and statistically significant at the 5% level ($\beta = -0.552$). In the under-investment subsample, CEI shows no significant effect on IE ($\beta = -0.116$, $p > 0.10$), indicating that CEI does not directly influence underinvestment behavior. However, in the over-investment subsample, CEI is negative and statistically significant at the 5% level ($\beta = -0.759$), suggesting that firms with higher carbon emission intensity are more prone to overinvestment.

Table 5. Robustness Checks

Variables	System GMM		
	Baseline Model	Under-Investment	Over- Investment
L.IE	0.209* (1.77)	0.095*** (3.52)	0.241*** (4.22)
CEI	-0.552** (-2.10)	-0.116 (-1.05)	-0.759** (-2.10)
TOBIN	-0.394*** (-2.93)	0.264** (2.36)	-0.463** (-2.40)
SIZE	0.336*** (3.53)	0.032 (0.28)	0.590* (1.87)
TANG	0.956 (0.80)	2.919*** (3.02)	3.434 (1.17)
FINSLACK	-2.261 (-1.11)	1.695 (1.18)	-15.158*** (-2.99)
AGE	0.276* (1.96)	0.167 (1.33)	0.068 (0.19)
LEV	1.058 (0.97)	-1.753* (-1.71)	-6.308** (-2.02)
Constant	-16.325*** (-3.42)	-7.031** (-2.12)	-20.552** (-2.42)
Observations	5,399	3,287	2,112
Number of Firms	925	767	639
F - value	54.50***	85.53***	54.13***
AR(1) test (p value)	0.000	0.000	0.000
AR(2) test (p value)	0.103	0.332	0.102
Hansen test of over-identification (p value)	0.550	0.469	0.713

Note: t-statistics are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All estimations include fixed effects for year, industry, and country.

Model validity is supported by diagnostic tests: AR(1) tests were significant ($p = 0.000$) in all models, while the insignificant p-values in AR(2) tests ($p = 0.103$, 0.332 , 0.102) indicate the absence of second-order autocorrelation (Arellano and Bond, 1991). Hansen's over-specified model test p-values are 0.550 , 0.469 , and 0.713 , respectively, confirming the validity of the selected instrument set (Hansen, 1982). These results show that the direction and significance

level of the relationship obtained in the basic analysis are similarly preserved in the System GMM estimates, thus demonstrating that the negative effect of CEI on IE is methodologically sound and reinforces the overall robustness of the findings.

To further ensure robustness, we employ three alternative measures of IE, with the corresponding results presented in Appendix Table A1. The findings remain consistent across all specifications. Moreover, we separately examine the effects of Scope 1 and Scope 2 emissions using both the OLS model and the System GMM method. The results, shown in Appendix Table 2, reveal a negative and significant effect of both Scope 1 and Scope 2 emissions on IE. Overall, these analyses corroborate our baseline results and demonstrate robustness

4.4. Moderation Analysis

This section presents the results of moderation analyses conducted to examine the possible regulatory effects of analyst coverage and environmental innovation variables on the CEI–IE relationship (Table 6).

Table 6. The Moderating Role of Analyst Coverage and Environmental Innovation in the CEI-IE Relationship

Variables	IE (1)	IE (2)
CEI	-0.176*** (-3.58)	-0.185*** (-4.91)
AnalystCoverage	0.034*** (3.40)	
CEI * AnalystCoverage	-0.012* (-1.83)	
EnvironmentalInnovation		0.006*** (5.95)
CEI * EnvironmentalInnovation		-0.003*** (-4.45)
TOBIN	-0.422*** (-7.89)	-0.383*** (-7.27)
SIZE	0.166** (2.51)	0.255*** (4.52)
TANG	0.643 (0.88)	0.627 (0.93)
FINSLACK	-2.464* (-1.83)	-2.439* (-1.91)
AGE	0.390*** (5.17)	0.374*** (5.75)
LEV	-1.179* (-1.90)	-1.258* (-1.89)
Constant	-7.921*** (-7.02)	-9.832*** (-10.64)
Observations	5,432	5,500
R-squared	0.149	0.145
Number of groups	907	931
F - value	559.6***	359.2***

Note: t-statistics are reported in parentheses. Significance levels are denoted as follows: ***p < 0.01, **p < 0.05, p < 0.10. All estimations include fixed effects for year, industry, and country.

The results of the regressions, which include analyst coverage and its interaction with CEI to investigate a potential moderating effect of analyst coverage on the CEI-IE relationship, are reported in column 1 of Table 6. In these analyses, CEI and analyst coverage have been mean-centered to prevent multicollinearity issues. Table 6 shows that analyst coverage has a positive effect on IE ($\beta=0.034$, $p<0.01$). On the other hand, the coefficient of the interaction term $CEI*AnalystCoverage$ is negative and statistically significant ($\beta=-0.012$, $p<0.10$), meaning that analyst coverage amplifies the negative effects of CEI on IE. This finding suggests that external monitoring by analysts may increase market pressure and increase the visibility of environmental risks, thereby exacerbating IE in carbon-intensive firms.

The results of the regressions which include environmental innovation and its interaction with CEI to investigate a potential moderating effect of environmental innovation on CEI-IE relationship are reported in column 2 of Table 6. In the analysis, CEI and environmental innovation have been mean-centered to prevent multicollinearity issues. Table 6 shows that environmental innovation has a positive effect on IE ($\beta=0.006$, $p<0.01$). In addition, the interaction term ($CEI*EnvironmentalInnovation$) is negative and significant at 1% level ($\beta=-0.003$), suggesting that for firms with high levels of environmental innovation, the deterioration in IE becomes more pronounced as CEI increases.

Additionally, separate moderation analyses were conducted at the Scope 1 (direct emissions) and Scope 2 (indirect emissions) levels, which are subcomponents of CEI. In these analyses, the moderating effects of analyst coverage and environmental innovation variables on the CEI-IE relationship were examined separately for each emission type. The findings obtained are generally consistent with the basic models and are presented in Appendix Table A3.

Moreover, figure 1 provides a visual representation of how environmental innovation influences the relationship between CEI and IE, offering a clearer understanding of this interaction.

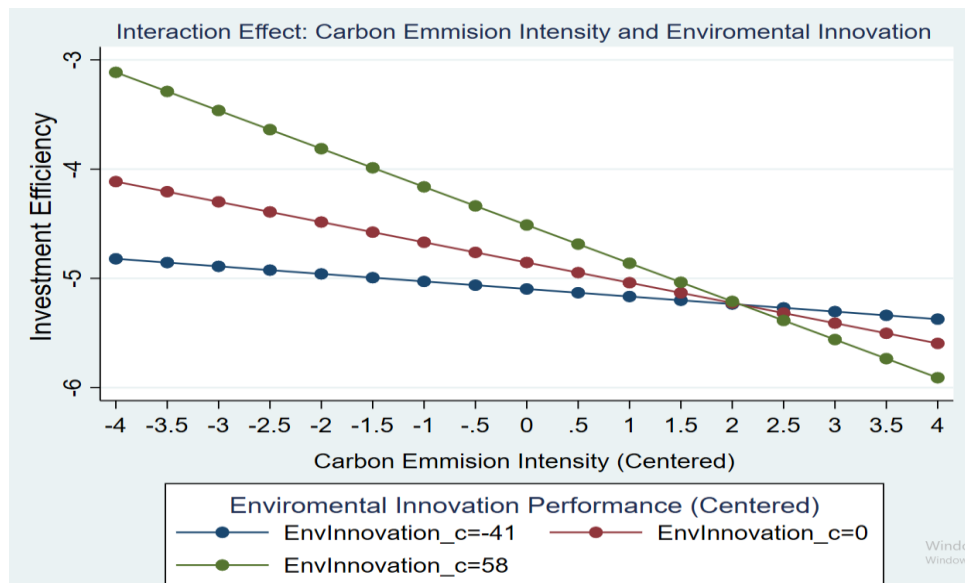


Figure 1. Heterogeneous Effects of Environmental Innovation on the Carbon Emission Intensity–Investment Efficiency Relationship

Figure 1 shows that firms with high levels of environmental innovation initially have a more advantageous position on IE. Especially up to a threshold point where the centralized value of CEI is approximately 2, these firms perform relatively more efficiently in their investment decisions. However, once this threshold is exceeded, meaning that CEI reaches very high levels, a notable decline in IE is observed among firms with high environmental innovation.

4.5. Heterogeneity Analysis

The impact of CEI on IE may vary across firms. Accordingly, we consider green revenue and ETS participation as potential factors that may influence this relationship, and the results are presented in Table 7. The first column indicates that for firms with high green income (i.e., firms with green income levels above the sample median) CEI does not have a significant effect on IE. However, the second column shows that for firms with low green income, the relationship between CEI and IE is significant and negative ($\beta=-0.253$ and $p<0.01$). This finding indicates that green income mitigates the negative impact of CEI on IE. Regarding ETS participation, column 3 of Table 7 shows that for firms participating in ETS, CEI does not have a significant effect on IE. However, column 4 shows that for firms that are not participating in ETS, the association between CEI and IE is negative and significant ($\beta=-0.187$ and $p<0.01$).

Table 7. Heterogeneous Effects of Green Revenue and ETS on the CEI–IE Relationship

Variables	Green Revenue		Emission Trading System Green Revenue	
	High	Low	Included	Not Included
CEI	0.054 (0.33)	-0.253*** (-3.21)	-0.153 (-1.29)	-0.187*** (-4.94)
Constant	-9.202** (-2.72)	-13.816*** (-6.78)	-9.981 (-1.05)	-10.972*** (-8.64)
Control Variables	Included	Included	Included	Included
Observations	1,951	3,550	1,123	4,356
R-squared	0.146	0.168	0.192	0.150
Number of firms	397	617	191	856
F - value	393.7***	576***	114.8***	210.5***

Note: t-statistics are reported in parentheses. Significance levels are denoted as follows: *** $p < 0.01$, ** $p < 0.05$, $p < 0.10$. All estimations include fixed effects for year, industry, and country. The table presents coefficients of the main explanatory variables only; control variable coefficients are excluded for clarity.

Finally, the impact of CEI on IE is analyzed in the context of sectoral differences. Table 8 shows that this relationship varies significantly across sectors. The negative and statistically significant effect of CEI on IE is observed across several sectors, including Consumer Non-Cyclicals ($\beta=-0.658$ and $p<0.01$), Consumer Cyclicals ($\beta=-0.244$ and $p<0.10$), Basic Materials ($\beta=-0.204$ and $p<0.10$), and Technology ($\beta=-0.300$ and $p<0.10$). In contrast, the relationship is positive and significant in Utilities ($\beta=0.947$ and $p<0.05$), suggesting that the regulatory structure and investment dynamics of the sector operate differently. The effects are not statistically significant in the Healthcare, Industrials, Real Estate, and Energy sectors. These results suggest that CEI may affect sector-specific investment decisions at different levels and that policy recommendations should be developed on a sectoral basis.

Table 8. Sectoral Heterogeneity in the Effect of CEI on IE

Variables	Basic Materials	Consumer Cyclicals	Consumer Non-Cyclicals	Energy	Healthcare
CEI	-0.204* (-1.95)	-0.244* (-2.06)	-0.658*** (-7.56)	-0.351 (-1.30)	-0.197 (-1.10)
Constant	-8.620** (-2.54)	-14.250*** (-3.07)	-13.378*** (-3.50)	-29.843*** (-3.36)	-9.525** (-2.18)
Control Variable	Included	Included	Included	Included	Included
Observations	754	963	405	258	489
R-squared	0.131	0.084	0.203	0.391	0.110
Number of Firms	100	157	70	39	88
F - value	27.87	188.9	1160	3421	2255
Variables	Industrials	Real Estate	Technology	Utilities	
CEI	0.070 (0.84)	-0.190 (-1.20)	-0.300* (-2.03)	0.947** (2.52)	
Constant	-9.512*** (-10.16)	6.406 (1.21)	-25.947*** (-8.93)	-90.296*** (-3.37)	
Control Variable	Included	Included	Included	Included	
Observations	1,318	343	862	109	
R-squared	0.098	0.106	0.143	0.831	
Number of Firms	219	73	168	17	
F - value	271.1	75649	983.3	537.7	

Note: t-statistics are reported in parentheses. Significance levels are denoted as follows: ***p < 0.01, **p < 0.05, p < 0.10. All estimations include fixed effects for year and country. The table presents coefficients of the main explanatory variables only; control variable coefficients are excluded for clarity.

5. Conclusion

5.1. Discussion of Main Findings

This study investigated the impact of CEI on IE and the moderating role of analyst coverage and environmental innovation in this relationship using data from 931 European firms for the period 2008-2023. Our analysis consistently showed that CEI has a negative impact on IE and that this negative effect manifests itself in the form of overinvestment. This result supports the agency theory, which suggests that managers in carbon-intensive firms tend to direct their free cash flows to low-return projects as a form of empire building or to symbolic environmental investments (Jensen and Meckling, 1976; Cariola et al., 2005; Lyon and Maxwell, 2011; Souguir et al., 2024). Moreover, our main finding is in line with the information asymmetry theory, which suggests that heightened uncertainty surrounding high-CIE firms leads to a higher cost of capital, thereby reducing IE (Myers and Majluf, 1984; Bao and Motlagh, 2024; Gulen and Ion, 2016). Supporting this interpretation, recent studies reveal that the increase in Scope 1 and 2 emissions encourages excessive investments that lead to inefficient use of resources, and that this process is closely related to agency problems between managers and shareholders (Jebri et al., 2024). Furthermore, the negative impact of carbon risk on IE appears to be amplified by the intensity of environmental uncertainties, deficiencies in corporate governance, and ineffective climate strategies (Luo et al., 2025).

Building on these baseline findings, our results show that an increase in the number of analysts following a company strengthens the negative relationship between CEI and IE. While analysts are important information intermediaries that increase efficiency in capital allocation by reducing information asymmetry (To et al., 2018), this role may operate differently in high-risk contexts. Greater analyst coverage may increase the market visibility of carbon risks, creating pressure on managers to focus on short-term performance, which can lead to the postponement of long-term environmental investments (Chan and Hameed, 2006; He and Tian, 2013; Qian et al., 2019). This interpretation is in line with prior studies linking greater analyst coverage to “short-termism” (DesJardine, 2015) and “greenwashing” (Gao and Chen, 2024). However, because our study does not directly measure managers’ intentions, these interpretations should be regarded as tentative rather than definitive.

In addition to analyst coverage, we found that the adverse effect of CEI on IE is more pronounced among firms with higher levels of environmental innovation. A possible explanation is that some firms employ environmental innovation as a symbolic legitimacy strategy rather than as a real transformation of production processes (Jebri et al., 2024). This pattern is also consistent with the literature on greenwashing, which suggests that firms highlight their environmental initiatives merely to improve their image while avoiding costly operational transformations (Delmas and Burbano, 2011; Hawn and Ioannou, 2016). While such strategies may create positive impressions among investors, they do not necessarily deliver real improvements in efficiency or reductions in carbon emissions (Jebri et al., 2024). From a theoretical perspective, this finding contradicts the resource-based view and the Porter Hypothesis, which suggest that innovation should increase efficiency. Our evidence shows that when environmental innovation is not supported by real technological changes, its potential to improve efficiency is constrained and can even be counterproductive.

Beyond these institutional mechanisms, our study reveals that the negative impact of CEI on IE is less pronounced for firms with higher levels of green revenue. This can be explained by the fact that firms with high green income levels can more easily adapt to both regulatory pressures and investor expectations, gain strategic flexibility, and act more rationally in capital allocation. On the other hand, firms with low green income levels face higher environmental risk perception, regulatory uncertainty, and external financing costs in the face of increasing CEI, which significantly weakens IE. This result is consistent with previous studies showing a positive relationship between green revenue and financial performance (Guo and Zhong, 2023; Kruse et al., 2020; Klausmann et al., 2025; Yan and Yin, 2023). Indeed, Matsumura et al. (2014) and Bolton and Kacperczyk (2021) show that carbon emissions have negative effects on firm value and cost of capital, while firms with high environmental performance gain advantages in investor confidence and market value. In this context, companies with a high green revenue ratio are perceived by the market as lower risk and can maintain their investment activities thanks to more favorable financing conditions.

Consistent with this line of evidence, the findings show that the negative impact of the CEI on IE is only significant for companies operating outside the ETS scope; conversely, this effect is weakened for companies included in the ETS. This finding is consistent with the literature suggesting that the market-based structure of the ETS improves firms’ resource allocation and makes investment decisions more rational by incorporating carbon costs into the price mechanism. Indeed, Sun et al. (2022) and Ren et al. (2022) show that ETS implementation increases firms’ financial performance and innovation capacity, while Vu et al. (2025) show that

ETS participation strengthens firms' resilience to carbon transition risks. Similarly, Chen et al. (2022) and Wang and Zhang (2024) show that ETS increases IE by limiting excessive and insufficient investment, while Ma et al. (2023) demonstrate that regulation improves the efficiency of labor investments. Additionally, the long-term positive effects of market-based environmental policies on energy and IE also support these findings (Dai and Li, 2023).

Finally, the sectoral analysis indicates that the impact of CEI on IE varies across sectors, with this effect being more pronounced in the consumer goods, basic materials, and technology sectors. This situation is closely related to the structural characteristics of the sectors. In the consumer goods sector, brand reputation and consumer sensitivity (Delmas and Burbano, 2011; Krüger, 2015) show that high CEI increases market and reputation risks, thereby raising capital costs. In the basic materials sector, high capital intensity and process emissions (Dechezleprêtre and Sato, 2017) restrict low-carbon transition investments, and in the technology sector, energy-intensive digital infrastructures become more vulnerable under increasing regulatory pressures.

5.2. Policy Implications

The evidence of a negative relationship between CEI and IE suggests that a comprehensive green policy framework is needed to mitigate the negative effects of carbon risk on IE and increase the efficiency of capital allocation. A central priority should be the integration of carbon pricing mechanisms (such as carbon taxes, ETs, or border carbon adjustments) into the market structure. Such an approach could redirect capital flows to low-carbon investments and make high-CEI projects less attractive (Iovino et al., 2021). In parallel, the widespread adoption of green financing instruments is critically important. Green bond issuances, in particular, facilitate the financing of environmentally friendly projects and alleviate companies' overinvestment problems (Jebri et al., 2024). Encouraging the financial system in this direction will strengthen not only environmental sustainability but also the quality of long-term investments. At the policy level, the EU Clean Industry Deal announced by the European Union in 2025 exemplifies this approach by providing tools such as accelerated depreciation, targeted tax credits, and green transition funds that support investments in low-carbon technologies (European Commission, 2025). Such policies have the potential to indirectly increase firms' IE by internalizing carbon costs and lowering financing costs. Extending similar policies to candidate or neighboring economies, such as Türkiye, could facilitate alignment with the EU green taxonomy, reduce firms' cost of access to capital markets, and facilitate diffusion of sustainable investment practices.

In line with these system-wide measures, it is equally important to address how external monitoring influences corporate investment behavior. Given our finding that broader analyst coverage intensifies the negative impact of CEI on IE, policymakers should develop regulatory mechanisms that limit short-term market pressures while preserving the information-providing role of analysts. First, standardized, forward-looking sustainability reporting, aligned with the EU's Corporate Sustainability Reporting Directive (CSRD), should be promoted. Such reporting would shift analysts' focus from short-term profits to long-term environmental performance (Zhang and Wu, 2023) and increase investor confidence by reducing capital costs (Dhaliwal et al., 2011). Second, subjecting disclosures to independent verification can help analysts distinguish symbolic claims from genuine environmental progress (Simnett et al., 2009; Christensen et al., 2021; Gao and Chen, 2024). Third, regulators and exchanges should encourage guidance based on long-term environmental metrics (e.g., emissions intensity, energy efficiency, green

investment ratio) rather than quarterly earnings guidance (He and Tian, 2013; Qian et al., 2019). At the corporate level, linking managerial incentives to verified decarbonization targets and institutionalizing environmental expertise in investment committees will enhance the sustainability of long-term investments even under analyst pressure (Guo et al., 2019; Zhang et al., 2023). Finally, methodological transparency should be provided regarding how environmental metrics used in analyst reports (e.g., CEI, Scope 1–3 emissions, transition plan quality) are modeled. This will enable assessments to be free from short-term pricing pressures and more aligned with sustainability goals (Qian et al., 2019; Zhang et al., 2023).

Extending these considerations to the domain of environmental innovation, firms should build their environmental innovation strategies on concrete practices that provide measurable carbon reductions, not just image-oriented ones, and should rely on transparency and impact-based reporting in this process. To achieve this, policymakers must ensure that innovation-related incentives and disclosures are designed to distinguish real operational transformations from symbolic actions. For example, tax credits, subsidies, or R&D grants should be tied to verified emission reductions and technological improvements, rather than self-reported innovation announcements. In addition, sustainability reporting frameworks should require firms to disclose the carbon impact of their innovation activities, enabling investors to assess whether environmental innovations result in measurable efficiency gains. Finally, corporate governance mechanisms are needed to align environmental innovation with efficiency gains. Measures such as establishing sustainability committees within boards or linking executive compensation to reduced carbon emission targets may ensure that environmental innovation becomes a tool for real transformation rather than a symbolic legitimacy tool.

Our finding that firms with higher levels of green revenue are less negatively affected by CEI highlights the importance of coordinated implementation of comprehensive mechanisms aimed at increasing the share of green revenue at the policy level. First, the introduction of financial incentives such as accelerated depreciation or tax breaks for low-carbon investments can accelerate the transition of businesses to clean production technologies (Brühl, 2021). Second, the allocation of approximately €38 billion by the EU Innovation Fund during the 2020–2030 period to support the commercialization of innovative low-carbon technologies (European Commission, 2025) demonstrates the importance of developing similar green R&D grants and credit mechanisms at the national level. Third, the public sector's creation of demand for low-carbon products and services through Green Public Procurement (GPP) policies can strengthen the private sector's motivation to invest in these areas (OECD, 2023). In conclusion, strengthening the green revenue structure will both increase companies' resilience to carbon risk and contribute to sustainable growth by supporting IE.

Our evidence that the adverse impact of CEI on IE is weaker for firms covered by the ETS highlights the importance of gradually expanding the scope of the ETS, maintaining a predictable and stable carbon price signal, restructure allocation and auction mechanisms based on efficiency principles, and effectively coordinating complementary policy instruments such as innovation funds and green R&D programs. The inclusion of new sectors such as shipping, aviation, and buildings under the EU's Fit for 55 reform package enhances the comprehensiveness of the carbon price signal in the economy, thereby strengthening emission reductions and capital allocation (European Council, 2023). The predictability of the carbon price signal reduces the financial risk of low-carbon investments, facilitating the mobilization of private capital; indeed, the literature shows that price uncertainty delays companies' decarbonization investments (Flues and van

Dender, 2020; Fuchs et al., 2024; van der Ploeg, 2021). Furthermore, directing ETS revenues toward green R&D and clean technology investments through mechanisms such as the Innovation Fund contributes to accelerating the low-carbon transition (European Commission, 2024). Therefore, this integrated policy approach will strengthen companies' resilience to carbon transition risks while limiting CEI-related inefficiencies and encouraging sustainable investment decisions.

Finally, the sectoral heterogeneity we identified in the CEI–IE relationship indicates the necessity of a sector-based transition policy framework that will increase IE while also supporting progress toward carbon reduction targets. In the basic materials sector (e.g., steel, cement, and chemicals), given the high capital requirements and uncertainty risks associated with first-generation low-carbon technologies, scaling up the Carbon Contracts for Difference (CCfD) mechanism across Europe and providing demand assurance through Green Public Procurement (GPP) are of great importance. These tools can encourage companies to accelerate their investment decisions, thereby directing capital towards low-carbon and efficient areas (Richstein and Neuhoff, 2022; Lösch et al., 2022; Economics, 2019). In consumer sectors (Consumer Cyclical and Non-Cyclical), eco-design standards, carbon footprint labeling, and extended producer responsibility (EPR) applications must be made mandatory to enable the tracking of environmental impacts at every stage of the product life cycle. Such regulations can steer companies away from superficial “green” marketing strategies and toward real emission reductions and innovative production processes (Poore & Nemecek, 2018). In the technology sector, particularly regarding energy-intensive data centers, it is important to effectively implement the KPI-based reporting obligations defined under the revised Energy Efficiency Directive (EED 2023/1791) and to disseminate the European Commission Joint Research Center's (JRC) “EU Code of Conduct on Data Center Energy Efficiency” guide (CODES, 2022; Avgerinou et al., 2017). This framework can increase transparency in energy consumption and encourage renewable energy investments, enabling companies to allocate resources more efficiently and strengthen IE (Masanet et al., 2020). This policy framework offers a comprehensive approach with the potential to increase IE based on the structural differences between sectors. However, more detailed empirical and sectoral analyses are needed to gain a deep understanding of each sector's unique dynamics and institutional response mechanisms. This study discusses the impact mechanisms related to these sectors at a general level. Future research examining how the CEI–IE relationship differs at the sector and sub-sector levels, the level of interaction between policy instruments, and how factors such as firm size, technology intensity, and market structure shape this relationship could constitute an important research agenda.

5.3. Limitations and Further Study

Although the findings of this study offer important insights, certain limitations may guide future research. First, it was found that the negative impact of CEI on IE is more pronounced in companies with high levels of environmental innovation. A possible explanation is that some companies use environmental innovation as a form of greenwashing to gain legitimacy rather than as a real transformation to reduce carbon emissions. However, since greenwashing was not directly measured in the study, it remains unclear whether this relationship reflects symbolic legitimacy strategies or the delayed returns typically associated with R&D investments. To fill this gap, future research could employ more direct indicators of greenwashing based on the

difference between companies' environmental statements and their actual carbon emission performance, or methods that examine the discourse-action inconsistencies in sustainability reporting. Such an approach would reveal whether the impact of environmental innovation on IE reflects a genuine emission reduction process or a perceived green legitimacy strategy, thereby providing deeper and policy-relevant contributions to the literature on CEI–IE interactions.

Secondly, the findings reveal that the impact of CEI on IE varies across sectors. However, this study has addressed these differences at a broad, sectoral level. More detailed sectoral and sub-sectoral analyses are needed to better understand each sector's unique dynamics, institutional responses, and capital structure. In particular, future research could investigate how the CEI–IE is shaped by sub-sector characteristics as well as by factors such as technology intensity, market competition, and firm size that shape this relationship. Such an approach would allow deeper and context-sensitive contributions to the literature.

Finally, this study is limited to companies operating in the EU and does not include comparisons between countries that differ in corporate structures, investor profiles, and levels of environmental regulation. Research examining how the CEI–IE relationship varies across countries and under different market-based and rule-based environmental policies. Such an approach could contribute to a more comprehensive understanding of the impact of environmental risks on investment decisions. Furthermore, exploring the interactions between market mechanisms, sustainability reporting practices, and corporate governance structures at the country level could enable the development of more targeted and contextual policy recommendations aimed at improving investment quality in carbon-intensive sectors.

Declaration of Research and Publication Ethics

This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics

Researcher's Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Declaration of Researcher's Conflict of Interest

There is no potential conflicts of interest in this study.

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APPENDIX:

Table A1. Robustness Analyses with Alternative Measures of Investment Efficiency

Variables	Firm-Level Controls	Interaction Model with NEG	PPE-Based Investment
CEI	-0.150*** (-5.07)	-0.190*** (-5.66)	-0.119** (-2.66)
TOBIN	-0.304*** (-7.86)	-0.360*** (-6.12)	-0.007 (-0.38)
SIZE	0.146*** (6.22)	0.288*** (7.20)	0.246*** (8.25)
TANG	0.092 (0.22)	0.815 (1.06)	-6.389*** (-6.52)
FINSLACK	-3.331** (-2.78)	-1.982 (-1.57)	-1.614** (-2.86)
AGE	0.297*** (5.82)	0.322*** (4.42)	0.203** (2.92)
LEV	-0.759*** (-3.41)	-0.902 (-1.62)	-0.022 (-0.03)
Constant	-8.829*** (-11.28)	-12.638*** (-16.89)	-7.814*** (-8.00)
Year Effect	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes
Country Effect	Yes	Yes	Yes
Observations	5,501	5,501	5,320
R-squared	0.130	0.144	0.198
Number of groups	931	931	932
F - value	417***	444***	32.87***

Notes: This table reports the results of robustness analyses using three alternative approaches to measure investment efficiency (IE). In Model (1), financial control variables are added to the baseline specification to account for firms’ financial characteristics (Biddle et al., 2009). Model (2) employs an alternative estimation that differentiates investment behavior based on the sign of sales growth, following Bilyay-Doğan et al. (2024). Model (3) defines investment as the ratio of the annual change in tangible and intangible fixed assets to total assets in the previous year (Biddle et al., 2009; Benlemlih and Bitar, 2018). t-statistics are reported in parentheses. Significance levels are denoted as follows: ***p < 0.01, **p < 0.05, p < 0.10.

Table A2. Robustness Tests with Scope 1–2 Emission Intensities: Driscoll–Kraay and System GMM

Variables	Driscoll-Kraay Standard Errors		System GMM	
	IE	IE	IE	IE
L.IE			0.240*	0.275*
			(1.73)	(1.85)
Scope1	-0.121**		-0.753**	
	(-2.72)		(-2.02)	
Scope2		-0.106***		-0.809*
		(-3.10)		(-1.68)
TOBIN	-0.405***	-0.347***	-0.522***	-0.338***
	(-5.49)	(-5.58)	(-3.39)	(-2.77)
SIZE	0.353***	0.311***	0.394***	0.400***
	(5.53)	(5.68)	(3.12)	(3.52)
TANG	0.584	0.387	1.342	1.218
	(0.71)	(0.45)	(0.85)	(0.73)
FINSLACK	-1.766	-2.811	-1.286	-3.737
	(-1.10)	(-1.55)	(-0.54)	(-1.57)
AGE	0.318**	0.317**	0.244	0.069
	(2.96)	(2.89)	(1.50)	(0.44)
LEV	-0.949	-1.016	2.609*	3.558*
	(-1.23)	(-1.52)	(1.83)	(1.70)
Constant	-13.118***	-11.552***	-24.877***	-19.065***
	(-11.05)	(-15.34)	(-3.31)	(-2.63)
Year Effect	Yes	Yes	Yes	Yes
Industry Effect	Yes	Yes	Yes	Yes
Country Effect	Yes	Yes	Yes	Yes
F - value	610.1***	493.8***	55.55***	36.25***
R-squared	0.136	0.140	-	-
Observations	4952	4914	4,864	4,829
Number of firms	875	880	871	876
AR(1) test (p value)	-	-	0.000	0.000
AR(2) test (p value)	-	-	0.100	0.104
Hansen test of over-identification (p value)	-	-	0.752	0.557

Notes: This table presents the results of additional robustness analyses examining the effects of Scope 1 (direct) and Scope 2 (indirect) emission intensities on IE using both the OLS model with Driscoll–Kraay standard errors and the System GMM estimator. The findings indicate that both emission types have a negative and statistically significant impact on IE, confirming the robustness of the baseline results. t-statistics are reported in parentheses. Significance levels are denoted as follows: ***p < 0.01, **p < 0.05, p < 0.10.

Table A3. The Moderating Role of Analyst Coverage and Environmental Innovation on the Relationship Between Scope 1–2 Emission Intensity and Investment Efficiency

Variables	Independent Variable: Investment Efficiency			
	Scope-1	Scope-2	Scope-1	Scope-2
CEI	-0.090*	-0.158**	-0.105**	-0.153***
	(-2.12)	(-2.75)	(-2.86)	(-5.45)
AnalystCoverage	0.027**	0.033**		
	(2.39)	(2.62)		
CEI_ AnalystCoverage	-0.010**	-0.017		
	(-2.45)	(-1.70)		
EnvironmentalInnovation			0.005***	0.005***
			(3.59)	(3.70)
CEI _EnvironmentalInnovation			-0.004***	-0.004***
			(-4.17)	(-4.00)
TOBIN	-0.451***	-0.414***	-0.410***	-0.371***
	(-6.35)	(-6.74)	(-5.64)	(-5.79)
SIZE	0.208**	0.180*	0.284***	0.278***
	(2.31)	(2.14)	(4.29)	(5.08)
TANG	0.487	0.661	0.376	0.599
	(0.57)	(0.77)	(0.50)	(0.79)
FINSLACK	-1.761	-1.884	-1.795	-1.979
	(-1.05)	(-1.23)	(-1.13)	(-1.35)
AGE	0.336***	0.320**	0.312***	0.306**
	(3.05)	(2.73)	(3.12)	(2.99)
LEV	-1.008	-1.065	-1.110	-1.185
	(-1.40)	(-1.61)	(-1.45)	(-1.70)
Constant	-8.549***	-7.630***	-10.193***	-9.725***
	(-6.01)	(-4.81)	(-10.25)	(-12.01)
Observations	4,828	4,812	4,889	4,873
R-squared	0.144	0.146	0.141	0.143
Number of groups	846	849	868	872
F - value	386.9	534.9	1430	588.6

Notes: This table analyzes the impact of carbon emission intensity (CEI) on investment efficiency separately based on direct (Scope 1) and indirect (Scope 2) emissions. Scope 1 emission intensity is calculated as the natural logarithm of the ratio of direct CO₂ emissions from the company's own activities to net sales revenue. Scope 2 emission intensity is defined as the natural logarithm of the ratio of CO₂ emissions from indirect energy sources such as purchased electricity, heat, or steam to net sales revenue. The models test the moderating effects of analyst coverage and environmental innovation variables on the CEI–IE relationship. Values in parentheses indicate t-statistics, while ***, **, and * denote significance levels of 1%, 5%, and 10%, respectively. Year, industry, and country fixed effects were controlled for in all models, and standard errors were estimated using the Driscoll–Kraay method.