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THE IMPACT OF CLIMATE RESILIENCE ON BANKS' FINANCIAL STABILITY

İklim Dayanıklılığının Bankaların Finansal Sağlamlığı Üzerindeki Etkisi

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Keywords: Climate Resilience, Financial Stability, AMG.

JEL Codes: G20, G21, G28, Q54, Q58.

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.

Anahtar Kelimeler: İklim Dayanıklılığı, Finansal İstikrar, AMG.

JEL Kodları: 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 sınırlandırmalıdır. 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 şiddetin/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.

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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 formula[1]:

$$Z = Ln[(ROA + (Equity / Assets)) / \sigma(ROA)] \tag{1}$$

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.

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[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.

$$ND-GAIN\ score\ =\ (Readiness\ score\ -\ Vulnerability\ score\ +\ 1)\ \times\ 50 \qquad (2)$$

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 countries[2] 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).

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[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.

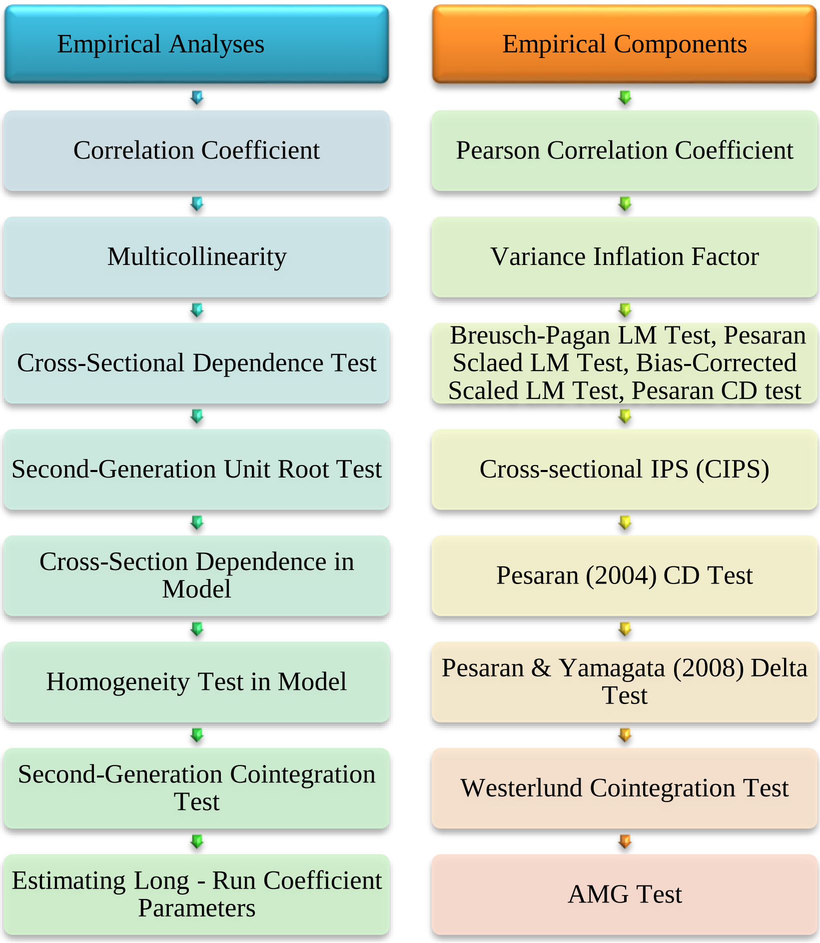

Figure 1. Analysis Process Steps

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 0.4394	1.0000 -				
CO2	-0.0583** 0.0269	0.4567* 0.0000	1.0000 -			
GDPG	0.1003* 0.0001	-0.1878* 0.0000	-0.0620** 0.0186	1.0000 -		
EFI	0.0903* 0.0006	0.7589* 0.0000	0.1387* 0.0000	-0.1266* 0.0000	1.0000 -	
PS	-0.0025 0.9246	0.5764* 0.0000	-0.0082 0.7545	-0.0957* 0.0003	0.5631* 0.0000	1.0000 -

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 Stat.	13129.29	89.732	86.304	12.815
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
CRI	Test Stat.	27349.53	238.637	235.209	63.704
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
GDPG	Test Stat.	24560.55	209.432	206.004	135.236
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
CO2	Test Stat.	24654.34	210.414	206.986	10.586
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
EFI	Test Stat.	18936.03	150.536	147.108	17.393
	p Value	0.0000*	0.0000*	0.0000*	0.0000*
PS	Test Stat.	14014.05	98.997	95.568	0.885
	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.

$$\Delta \mathrm{yit} = \alpha i + \beta i y i, t - 1 + \gamma i\, \bar{y} t\ - 1 + \delta i \Delta\, \bar{y} t + \sum_{j=1}^{pi} \phi_{\mathrm{ij}} \Delta \mathrm{y}_{\mathrm{i,t-j}} + \varepsilon_{it} \tag{5}$$

where; Δ= the first-difference operator, y_{it}= the variable of interest for cross-section i at time t, $\bar{y}_t$ = $1/N \sum_{i=1}^{N} y_i$ = 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:

$$CIPS = 1/N \sum_{i=1}^{N} t_i \tag{6}$$

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(O)	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:

$$\mathrm{CD} = \sqrt{2T/N(N-1)}\left(\sum_{i=1}^{N-1} 0 \sum_{j=i+1}^{N} p_{ij}\right) \tag{7}$$

Pesaran and Yamagata standardized S as follows:

$$\Delta = \left[\sqrt{N(\mathrm{S}-\mathrm{kN})}/\sqrt{2\mathrm{kN}})\right]/1 \tag{8}$$

Table 7. Cross-Section Dependence and Homogeneity Test in Model

Pesaran (2004) CD Test	Pesaran and Yamagata (2008)	
CD = 8.35	Δ= 11.844	Δ_{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:

$$yit \;=\; \alpha i \;+\; \beta i'\, xit \;+\; \gamma i\, \bar{y}t \;+\; \delta i'\, \bar{x}t \;+\; \varepsilon it \tag{9}$$

where; y_{it} is the dependent variable, x_{it} is a vector of explanatory variables, $\bar{y}t = (1/N)\, \Sigma_i\, y_{it}$ and $\bar{x}_t = (1/N)\, \Sigma_i\, x_{it}$ 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:

$$\Delta yit = ct + \Delta xit' \beta + \varepsilon it \tag{10}$$

From this regression, obtain the common dynamic effect, denoted as $\hat{c}_t$. Include this common factor in the country-specific regressions:

$$yit = \alpha i + \beta i' xit + \lambda i \hat{c}t + \varepsilon it \tag{11}$$

Then the AMG estimator is the mean of the individual slope coefficients:

$$\beta AMG = (1/N) \Sigma i\beta I \tag{12}$$

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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