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DRIVERS OF CO_2 EMISSIONS: EVIDENCE FROM BANKING, DIGITALIZATION, AND RESOURCE DEPLETION*

CO_2 Emisyonlarının Belirleyicileri: Bankacılık, Dijitalleşme ve Doğal Kaynak Tükenmesinden Bulgular

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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.

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

JEL Codes: Q01, Q53, G21, O39, Q34.

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 arttırdığına 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 bulundurarak, bulgularla tutarlı ve tamamlayıcı nitelikte önemli politika önerileri sunarak literatüre katkıda bulunuyoruz.

Anahtar Kelimeler: Sürdürülebilir Kalkınma, CO_2 Emisyonları, Bankacılık, Dijitalleşme, Doğal Kaynak Tükenmesi

JEL Kodları: Q01, Q53, G21, O39, Q34.

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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 CO_2 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 CO_2 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 CO_2 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 CO_2 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 CO_2 is worthy of examination.

Natural resources have a significant multiplier effect on CO_2 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 CO_2 are analyzed. Finally, the model used is unique in the literature. Banking and digitalization indices were generated as independent variables to explain CO_2 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 (CO_2)

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.

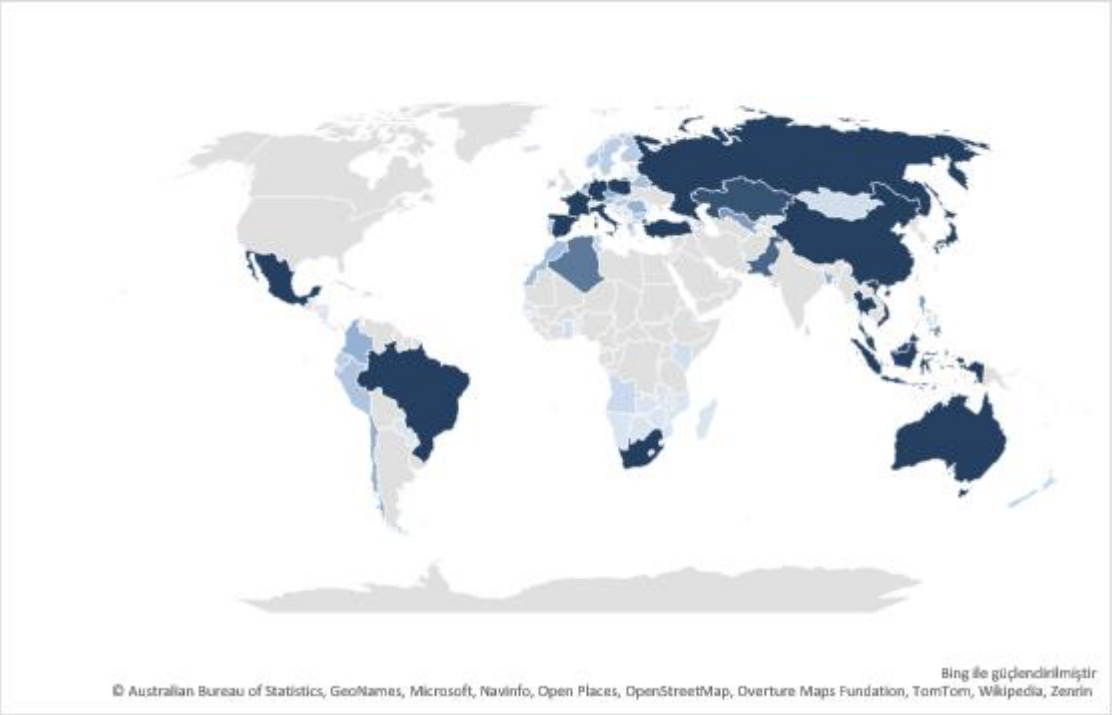

Figure 1. Per Capita Carbon Emission (CO_2) Map
Source: Created by the authors using World Bank data.

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:

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

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), CO_2 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 80% 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 Brahmasrene (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 (CO_2). The interpretation of the environmental Kuznets curve in terms of digitalization indicates that CO_2 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. Haldar 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 CO_2 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 CO_2 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 CO_2 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 CO_2. 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 CO_2 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 CO_2 emissions. Fourth, no study in the literature addresses the complex structure of banking, digitalization, natural resource depletion, and CO_2 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 CO_2 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:

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

H_0: Digitalization has no significant impact on the environment (β_1=0)

H_1: 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 (β_1>0, β_2<0)

H_2: The impact of digitalization on the environment supports the rebound effect, which states that increased productivity will increase demand (β_1>0, β_2>=0)

H_3: Banking does not have a significant impact on the environment (β_3=0).

H_4: The environmental impact of banking supports the green finance approach, which argues that environmental damage will be reduced through green banking regulations (β_3<0).

H_5: 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 (β_3>0).

H_6: The impact of natural resource depletion on the environment supports the view that environmental destruction will increase as resources decrease (β_4>0).

If the H_0 hypothesis can be rejected, the H_1 hypothesis supports the environmental Kuznets curve interpretation, while the H_2 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, CO_2 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)
ELRENW	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 (CO_2)

The dependent variable of this study is per capita CO_2, which is widely used in the literature to measure environmental pollution. Adha et al. (2023) use CO_2 emissions to measure the environmental impacts of information and communication technologies. Afjal et al. (2023) measure the impact of internet use on CO_2 by substituting digitalization. Xu et al. (2023) investigated the impacts on CO_2 in their study on green finance and fintech; while studies such as Yang et al. (2024) and Pu et al. (2024) used CO_2 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 CO_2 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 CO_2 emissions. For example, Valadkhani et al. (2019) compared the CO_2 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 CO_2 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 CO_2 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 CO_2 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 CO_2 emissions. The abbreviations ELOGC are used for non-renewable energy production and ELRENW for renewable energy production.

3.1.6. Industrial Production

Industrial production per worker is frequently used in the literature to explain CO_2 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 CO_2 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 CO_2/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 CO_2 emissions per capita. The accepted view in the literature is that an increase in industrial production per worker leads to an increase in CO_2 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	ELRENW	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		
ELRENW	-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
	overall	3.4947	1.9962	-1.2385	9.4507
CO_2	between		2.0036	-1.1264	9.3443
	within		0.0873	3.0867	3.7756
	overall	0.0188	2.7394	-8.0545	8.0576
DIGI	between		2.7400	-7.8257	7.6558
	within		0.2580	-1.3932	1.0776
	overall	0.0495	1.1345	-2.8478	3.2460
BANK	between		1.1208	-2.7218	2.3982
	within		0.2063	-0.9184	1.0789
	overall	7.9818	2.1754	0.3884	13.8433
NATDEP	between		2.0742	2.5221	13.1438
	within		0.6859	3.3006	11.3654
	overall	3.4179	1.8231	-6.4578	4.6051
ELOGC	between		1.8094	-6.0542	4.6033
	within		0.2836	-0.2499	6.2272
	overall	3.0540	1.4470	-2.1878	4.7648
ELRENW	between		1.4247	-1.7158	4.6078
	within		0.2877	1.3166	6.6037
	overall	10.0119	1.1242	7.3568	12.9941
IND_PW	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 CO_2 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 CO_2 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 CO_2 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, $\tau \in \{0.20, 0.40,\ 0.60\ ve\ 0.80\}$ represents the τth 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) ***
ELRENW	-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 boostrap 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 boostrap 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 CO_2 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 CO_2 and support the findings of studies providing findings supporting the rebound effect (Danish et al., 2018; Majeed, 2018; Freitgad 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 CO_2 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; Haldar 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 CO_2 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 CO_2 emissions from consumption sources, it will positively contribute to the environment by reducing CO_2 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 CO_2 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 CO_2 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 CO_2 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	Turkiye
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	