

Research Article

Digitalization and Financial Development as Drivers of Material Footprint: Evidence from Developing Countries

Malzeme Ayak İzinin Belirleyicileri Olarak Dijitalleşme ve Finansal Gelişme: Gelişmekte Olan Ülkelerden Kanıtlar

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Abstract

This study empirically examines the effects of digitalization and financial development on the per capita material footprint across 27 developing countries during the 2000-2023 period, within the framework of the STIRPAT model. The sample consists of countries classified as developing economies according to the World Bank's classification and for which complete data are available throughout the analysis period. Because the material footprint -a consumption-based indicator reflecting total resource use across supply chains- serves as a more comprehensive measure of environmental pressure in globalizing economies, it was used as the dependent variable instead of carbon emissions. Long-run coefficients were estimated using the Dynamic Common Correlated Effects Mean Group (DCCE-MG) estimator, which accounts for cross-sectional dependence and slope heterogeneity. Conditional median estimates were obtained using bootstrap MM-QR. Additional analyses based on a parsimonious specification are reported separately. Trade openness and the trade balance, both included as controls, have negative and statistically significant coefficients in both estimators. By contrast, per capita income, energy intensity, urbanization, and financial depth are positive and significant only in the MM-QR estimates. The negative MM-QR coefficient indicates that digitalization is associated with a lower material footprint at the conditional median. This finding suggests that digital infrastructure development may contribute to resource efficiency in developing economies. The results also differ across countries, indicating substantial heterogeneity within the sample. Accordingly, policy priorities concerning digitalization, institutional capacity, and the energy transition may need to be adapted to country-specific conditions.

Keywords: Material footprint, STIRPAT, digitalization, financial development, DCCE-MG, MM-QR

Öz

Bu çalışma, STIRPAT modeli çerçevesinde 2000-2023 döneminde 27 gelişmekte olan ülkede dijitalleşme ve finansal gelişmenin kişi başına malzeme ayak izi üzerindeki etkilerini ampirik olarak incelemektedir. Örneklem, Dünya Bankası sınıflandırmasına göre gelişmekte olan ekonomiler olarak tanımlanan ve analiz dönemi boyunca eksiksiz veriye sahip ülkelerden oluşmaktadır. Küreselleşen ekonomilerde çevresel baskının daha kapsamlı bir göstergesi olması nedeniyle, karbon emisyonları yerine tedarik zincirleri boyunca toplam kaynak kullanımını

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yansıtan tüketim temelli bir gösterge olan malzeme ayak izi bağımlı değişken olarak kullanılmıştır. Uzun dönem katsayıları, yatay kesit bağımlılığı ve eğim heterojenliğini dikkate alan Dinamik Ortak Korelasyonlu Etkiler Ortalama Grubu (DCCE-MG) tahmincisi ile elde edilmiştir. Koşullu medyan tahminleri bootstrap MM-QR yöntemiyle elde edilmiştir. Daraltılmış modele dayanan ek analizler ayrıca sunulmuştur. Kontrol değişkeni olarak kullanılan ticaret açıklığı ile ticaret dengesi, her iki tahmincide de negatif ve istatistiksel olarak anlamlıdır. Buna karşılık kişi başına gelir, enerji yoğunluğu, kentleşme ve finansal derinlik yalnızca MM-QR tahminlerinde pozitif ve anlamlıdır. Negatif MM-QR katsayısı, dijitalleşmenin koşullu medyanda daha düşük bir malzeme ayak iziyle ilişkili olduğunu göstermekte ve dijital altyapı gelişiminin gelişmekte olan ekonomilerde kaynak verimliliğini destekleyebileceğine işaret etmektedir. Sonuçlar, gelişmekte olan ülkelerde çevresel baskı belirleyicilerinin heterojen bir yapıya sahip olduğunu ortaya koymaktadır. Buna göre dijital dönüşüm, kurumsal kapasite ve enerji dönüşümüne ilişkin politika önceliklerinin ülke koşullarına göre belirlenmesi gerekmektedir.

Anahtar Kelimeler: Malzeme ayak izi, STIRPAT, dijitalleşme, finansal gelişme, DCCE-MG, MM-QR

1. Introduction

Production and consumption activities that have been fueled since the Industrial Revolution have exerted the greatest pressure on the global ecosystem. Humanity's current resource consumption exceeds the capacity of nature to regenerate, resulting in an ecological imbalance (Yılmaz, 2024, p. 638). The challenges of climate change, rapid biodiversity loss, and rapid depletion of natural resources call for nations to rethink their economic development models, with a focus on environmental sustainability. A literature survey revealed that carbon dioxide (CO₂) emissions are the most common measure of environmental pollution. Nevertheless, owing to the globalization of production processes and the growing complexity of supply chains, the emission indicators used to assess environmental impact have become inadequate. Hence, the material footprint, which reflects the total quantity of biomass, fossil fuels, metals, and non-metallic minerals required to satisfy the final demand of an economy, has been highlighted in the literature as a measurement instrument that conveys the impact of countries on natural resources (Regueiro-Ferreira & Alonso-Fernández, 2023, p. 2; Wiedmann et al., 2015, p. 6271).

Among the theoretical frameworks formulated to explain environmental degradation, the IPAT model (Impact = Population × Affluence × Technology), proposed by Ehrlich and Holdren (1971), is important. However, the assumption of this model that there is a direct proportionality between its variables, as well as its structure as a mathematical identity, which does not permit empirical hypothesis testing, has resulted in several critiques (York et al., 2003, p. 353). To address these problems, Dietz and Rosa (1994; 1997) developed the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, which is a stochastic version of the IPAT approach. The STIRPAT model permits the assessment of the nonlinear influences of population, affluence, and technology on the environment. Additionally, it provides the theoretical framework for this research by enabling the inclusion of variables such as financial development and digitalization (Topdağ et al., 2020, p. 344; Şentürk, 2023, p. 98).

Developing countries face a dilemma in ensuring environmental sustainability and achieving economic growth. In this regard, the idea that structural changes in variables such as digitalization and financial development negatively affect sustainable environmental goals has become a subject of debate in the literature. It has been argued that digitalization and technological advancement can reduce environmental pressures via efficient resource use, green production processes, and faster information flows (Hao et al., 2023, p. 2). However, communication and information technologies increase the material footprint due to their high energy consumption, the energy-intensive nature of data centers, and the increased generation of electronic waste (Anser et al., 2021, p. 21067). Similarly, financial development and money supply influence the environment. It may become easier to obtain green technologies as financial markets develop, thus reducing environmental degradation (Usman & Hammar, 2021, p. 15520). However, the expansion of consumer credit can increase the demand for energy-intensive products, thereby worsening environmental degradation (Chishti et al., 2021, p. 2).

The primary objective of this study was to empirically evaluate the effects of digitalization and financial development on the material footprint in developing countries using the STIRPAT model. Most studies have focused on CO₂ emissions. However, this study treats the material footprint as a dependent variable and aims to bridge the gap by incorporating money supply, digitalization, and financial development into the model. Population, per capita income, the digitalization index, and money supply are included

as explanatory variables, while energy intensity, sectoral value added, the rule of law, urbanization, trade openness, and the trade balance are included as control variables.

This study seeks to answer the question: “How do digitalization and financial development affect the material footprint in developing countries, and do these effects differ between the long-run mean and conditional median estimates?”

H1: Digitalization reduces the material footprint in developing countries.

H2: Financial development increases the material footprint in developing countries.

H3: Per capita income and energy intensity increase the material footprint.

H4: The effects of digitalization and financial development differ between the long-run mean and conditional median estimates.

The first section introduces the study, while the second section reviews the relevant literature. The third section presents the data, methodology, and empirical findings. The final section concludes the study, discusses policy implications, and outlines directions for future research.

2. Literature Review

The IPAT (Impact = Population $\times$ Affluence $\times$ Technology) model was created by Ehrlich and Holdren (1971) to study how economic and demographic changes influence the environment and form the basis of theoretical approaches (Dietz & Rosa, 1997, p. 175). A stochastic version of the IPAT model was introduced because the IPAT model was considered inadequate for explaining environmental degradation. This section compares the variables used in the STIRPAT model with those employed in this study.

A review of previous research on environmental degradation reveals that most studies have focused on CO₂ emissions. The material footprint is now considered a more comprehensive indicator of environmental impact, as the complexity of supply chains and the dispersion of production activities across regions due to globalization have highlighted the limitations of production-based indicators (Wiedmann et al., 2015, p. 6271). In their research on whether economic growth and material use can be decoupled, Regueiro-Ferreira and Alonso-Fernández found that developed countries relocate production to other countries; thus, their domestic material footprint appears to decrease, but their imports increase (Regueiro-Ferreira & Alonso-Fernández, 2023, p. 1). These studies indicate that consumption-based measures such as the material footprint capture dimensions of environmental pressure that production-based indicators may overlook. However, the majority of existing studies focus on developed or OECD economies, leaving evidence from developing country panels relatively limited.

The environmental impacts of digitalization have been discussed in the literature in terms of the trade-off between environmental costs and higher efficiency. For example, the spread of information and communication technologies may exacerbate environmental degradation by increasing energy demand. Anser et al. (2021, p. 21067) stated that internet and mobile usage initially increased environmental degradation. However, the trend changed as the technological development leaned towards more efficient technologies. Khan et al. (2023, p. 2) contend that the inclusivity of digital finance may raise carbon emissions as it makes consumers more readily able to purchase energy-demanding products. However, some researchers argue that digitalization helps reduce environmental degradation. Hao et al. (2023, p. 2) mentioned that digitization helps to cut down resource consumption, makes production processes more efficient, and eventually leads to the development of a green regional economy through the support of a green transformation. Based on this reasoning, digitalization is a factor that lowers the level of environmental stress, and it is one of the "Technology (T)" components of the STIRPAT model. Sun et al. (2024, p. 2) revealed that corporate social responsibility practices and digital transformation have a positive impact on companies' environmental, social, and governance performance. These findings indicate that the environmental effects of digitalization may depend on the level of digital development, the structure of the economy, and the dimension of digitalization considered. Although carbon emissions have dominated the environmental literature, evidence on the relationship between digitalization and the material footprint remains sparse. It therefore remains unclear whether the efficiency gains associated with digitalization also reduce material resource use.

A review of the literature on financial development and the environment uncovers conflicting opinions. The growth of the financial system can improve environmental quality by providing companies with the capital needed to invest in environmentally friendly technologies (Usman & Hammar, 2021, p. 15520). Le et al. (2020, p. 2) indicated that financial inclusion stimulates technological innovation, which can reduce emissions. However, financial development may increase the demand for energy-intensive products by providing consumers with easier access to credit, thereby expanding their material consumption. Topdağ et al. (2020, p. 354) found that the financial development index was associated with a higher ecological footprint, a pattern also reported in subsequent studies. Similarly, Khan et al. (2023, p. 2) found that digital financial inclusion contributes to rising CO₂ emissions through the economic growth channel in developing countries. These findings suggest that financial development may operate through opposing channels. It can support green investment and technological innovation, but it may also expand resource-intensive consumption and production. Furthermore, the majority of studies in this field use carbon emissions as an environmental indicator and focus on middle- or high-income country groups. The impact of financial depth on material resource consumption in developing countries, however, has received comparatively little attention.

Energy use is an influential factor contributing to environmental degradation in the STIRPAT model. Yıldırım and Akın (2023, p. 338) examined 23 Organization for Economic Co-operation and Development (OECD) countries. They found that increases in energy intensity and non-renewable energy production were associated with higher CO₂ emissions. In contrast, renewable energy has a limited impact on emission reduction. Çamkaya (2024, p. 107), who conducted research in Türkiye, revealed that fossil fuel reliance and industrialization exacerbate environmental harm, while renewable energy use serves to alleviate this effect over time. Şentürk (2023, p. 102) remarked that energy consumption and trade openness raise carbon emissions in Türkiye in the long run and underlined the significance of a circular economy transition.

Population and income, the basic elements of the STIRPAT framework, largely determine the material footprint. Majeed and Tauqir (2020, p. 665) ascertained that population growth and urbanization are the leading causes of increased global emissions. However, in high-income countries, the negative environmental consequences of economic growth are effectively controlled. Yılmaz (2024, p. 649) in his research on Türkiye showed that the population has the greatest effect on the ecological footprint and that the rise in per capita income also contributes to this increase.

Besides, the rule of law and the level of institutional quality are the variables treated as controls in the model, which are the factors that significantly determine the effectiveness of environmental regulations. According to Erdoğan and Acaravcı (2022, p. 1884), well-functioning institutions control resource allocation more efficiently and positively impact economic performance. Therefore, it is assumed that in countries with strong legal infrastructure, where environmental regulations are enforced more effectively, the material footprint will be lower.

Finally, trade and urbanization, which are included as control variables, are also widely examined in the literature. Nathaniel (2020, p. 1510) revealed that urbanization and energy consumption are important factors leading to environmental degradation, while Destek and Sinha (2020, p. 1) argued that the impact of trade openness on the ecological footprint can be different from one country to another among the OECD countries. Evidence on the joint effects of digitalization and financial development within a material-footprint-based STIRPAT framework remains limited, particularly for developing-country panels. The material footprint has also received less attention than carbon emissions, and panel evidence that accounts for both cross-sectional dependence and slope heterogeneity remains limited. This study therefore examines digitalization and financial development for 27 developing countries over the 2000-2023 period, using the material footprint as the dependent variable and reporting DCCE-MG and bootstrap MM-QR estimates.

3. Data Set, Method and Findings

¹This study analyzes how digitalization and financial development affect the material footprint in 27 developing countries using World Bank data within the STIRPAT framework. The time span for the analysis is from 2000, the year when data on digitalization indicators started to be published regularly, to 2023, the year for which the latest data on energy and industry variables were available.

This study chose the material footprint per capita as the dependent variable. Material footprint data cover four categories: biomass, fossil fuels, metal ores, and non-metallic minerals. This study combined these four categories to obtain the total footprint. Then, it was divided by the population of the respective year to obtain per capita values.

The digitalization index was constructed using the internet penetration rate and fixed broadband subscriptions per 100 people, capturing both the accessibility and connectivity dimensions of digital infrastructure in developing countries. The internet penetration rate reflects the extent of access to digital technologies, while fixed broadband subscriptions represent the technical capacity and quality of the network infrastructure. These indicators were selected primarily because they provide continuous and comparable data across all 27 countries throughout the 2000-2023 period. More comprehensive measures -such as e-commerce volume, cloud computing usage, artificial intelligence adoption, or digital service density- are not consistently reported for many developing countries, particularly in earlier years. Nevertheless, internet and broadband indicators are well-established proxies for digital transformation in the environmental and digital economy literature (Anser et al., 2021; Hao et al., 2023). However, the index does not cover mobile platforms, the platform economy, cloud technologies, or other advanced digital services that have become more widespread since 2016. This limitation should be considered when interpreting the results. Future studies may use broader measures of digitalization. When forming the index, Z-score standardization was used for each indicator. The index was defined as follows $DIG_{it} = \frac{1}{2} \left(\frac{INT_{it} - \mu_{INT}}{\sigma_{INT}} + \frac{GB_{it} - \mu_{GB}}{\sigma_{GB}} \right)$ where μ_{INT} denotes the average ratio of internet users to the population, σ_{INT} denotes the standard deviation of the ratio of internet users to the population, μ_{gb} denotes the average number of fixed broadband subscriptions per 100 people, and σ_{GB} denotes the standard deviation of the number of fixed broadband subscriptions per 100 people. This index reflects the infrastructure and access dimensions of digital transformation, as it is measured by Internet usage and fixed broadband subscriptions.

We use the M2/GDP ratio because it is available consistently for all 27 countries over the 2000-2023 period, whereas private credit data are incomplete for some countries, particularly in the early years of the panel. The ratio also reflects the overall depth of the financial system through deposit money and quasi-money and has been used as a financial development indicator in the environmental economics literature (e.g., Topdağ et al., 2020; Usman & Hammar, 2021). The trade balance was calculated as exports minus imports of goods and services, expressed as a percentage of GDP. Positive values indicate a surplus, whereas negative values indicate a deficit. It is therefore treated as a trade variable rather than as a measure of natural resource dependence, natural resource rents, or resource efficiency. Energy intensity, the rule of law, industrial value added, urbanization, trade openness, and the trade balance were included as control variables. Table 2 presents a summary of the definitions, data sources, and information on the transformation of variables used in this study.

¹ Albania, Argentina, Azerbaijan, Belarus, Bosnia and Herzegovina, Brazil, Chile, China, Colombia, Costa Rica, Ecuador, Georgia, Iran, Jordan, Kazakhstan, Malaysia, Mexico, Moldova, Mongolia, Morocco, North Macedonia, Paraguay, Peru, South Africa, Thailand, Tunisia, and Türkiye.

Table 2: Information on Variables

Variable Type	Variable Name	Abbreviation	Definition	Source	Conversion/type
Material Footprint	Per capita material footprint	lnMFpc	An indicator obtained by dividing the total material footprint by the total population	UN IRP / Global Material Flows Database	Logarithm-dependent variable
STIRPAT-population	Total population	lnPOP	Total population	World Bank	Logarithm-independent variable
STIRPAT-welfare	Per capita income	lnGDPpc	Real income per capita (PPP, 2021 constant prices)	World Bank	Logarithm-independent variable
Technology	Digitalization index	DIG	A composite digitalization indicator based on internet usage and fixed broadband subscriptions	World Bank	Level/independent variable
Energy	Energy intensity	lnEL	Primary energy consumption per unit of GDP	World Bank	Logarithm/control variable
External Trade	Trade openness	TRD	Sum of exports and imports of goods and services as a percentage of GDP	World Bank	Level/control variable
External Trade	Trade balance	TB	Exports of goods and services minus imports of goods and services, as a percentage of GDP	World Bank	Level/control variable
Industrialization	Sector value added	IND	Share of the industrial and construction sectors in GDP	World Bank	Level/control variable
Urbanization	Urban population	URB	Ratio of urban population to total population	World Bank	Level/control variable
Institutional Quality	Rule of law	ROL	Rule of Law Index	World Bank	Level/control variable
Financial Development	Money supply	M2	Ratio of money supply (M2) to GDP	World Bank	Level/independent variable

The most fundamental version of the STIRPAT model used in this study is expressed in Equation 1.

$$\ln MFpc_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln GDPpc_{it} + \beta_3 DIG_{it} + \beta_4 M2_{it} + \sum \gamma_k Z_{kit} + e_{it} \quad (1)$$

where Z_{kit} denotes the k th control variable—energy intensity, trade openness, the trade balance, industrial value added, urbanization, and the rule of law—and γ_k is its corresponding coefficient.

To acquire the empirical results, the following methods were used: a) correlation analysis was conducted to reveal the simple relationships, b) the variance inflation factor (VIF) analysis was employed to detect multicollinearity, c) CD was analyzed, d) the Cross-sectionally Augmented Im-Pesaran-Shin (CIPS) unit root test was applied for stationarity analysis, e) the delta test was carried out, and f) the Westerlund (2007) panel cointegration test was applied to examine the long-run relationship among the variables g) coefficient estimates were obtained using the Dynamic Common Correlated Effects Mean Group (DCCE-MG) and the Bootstrap-based Method of Moments Quantile Regression (MM-QR) methods h) additional analyses based on a parsimonious specification are reported separately. The analyses were conducted with the help of the Stata software (version 17). The descriptive statistics of the variables are presented in Table 3.

Table 3: Descriptive Statistics

Variable	Mean	Standard deviation	Minumum	Maximum
lnMFpc	2.668808	1.304534	1.478878	8.797581
lnPOP	16.73827	1.522864	14.42076	21.06853
lnGDPpc	9.596558	0.414243	8.310424	10.41992
DIG	-0.0141	0.940904	-1.21682	2.66248
lnEL	1.484051	0.417981	0.647103	2.643334
TRD	78.44181	34.99146	21.85226	220.4068
TB	-3.92429	12.90169	-52.7841	42.30938
IND	30.33309	8.521927	16.87791	66.16033
URB	65.73691	14.03936	31.46262	92.40484
ROL	-0.29614	0.508643	-1.30366	1.348704
M2	62.11369	38.28301	10.38241	211.9725

The descriptive statistics reveal a great diversity of countries regarding economic, technological, institutional, and social indicators. Therefore, the use of heterogeneous panel data methods in the planned analyses is essential.

3.1. Pre-Tests and Diagnostic Analysis

Although correlation and VIF analyses are generally not required in panel data analyses, this study included them to preliminarily assess the risk of multicollinearity, given the relatively large number of variables. Therefore, the basic assumptions of the model were assessed before further analyses.

The correlation analysis was conducted to determine the strength and direction of the bivariate relationships between variables, which are presented in Table 4. The results indicate that none of the coefficients between the variables exceeded the threshold value of 0.80. According to Gujarati and Porter (2009), this signifies that there are no strong linear relationships between the variables. Additionally, it should be emphasized that the magnitude of the correlation coefficients does not imply any cause-and-effect relationship.

Table 4: Correlation Analysis

Variable	lnMFpc	lnPOP	lnGDPpc	DIG	lnEL	TRD	TB	IND	URB	ROL	M2
lnMFpc	1										
lnPOP	-0.265***	1									
lnGDPpc	0.150***	0.154***	1								
DIG	0.176***	0.038	0.613***	1							
lnEL	0.001	0.085**	-0.171***	-0.199***	1						
TRD	0.234***	-0.471***	-0.006	0.019	0.288***	1					

TB	−0.250***	0.469***	0.433***	0.062	0.013	−0.145***	1				
IND	−0.199***	0.323***	0.135***	−0.090**	0.342***	0.154***	0.673***	1			
URB	0.064	0.266***	0.463***	0.244***	−0.388***	−0.305***	0.248***	−0.086**	1		
ROL	0.114***	−0.025	0.188***	0.156***	−0.231***	0.171***	−0.044	−0.283***	0.232***	1	
M2	0.098**	0.445***	−0.041	0.214***	0.108***	0.175***	0.034	0.127***	−0.047	0.442***	1

Note: The *, **, and *** symbols next to the correlation coefficients in the table refer to significance levels of 10%, 5%, and 1%, respectively.

To complement the correlation findings presented in Table 4, Figure 1 displays scatter plots and linear fit lines depicting the bivariate relationships between the material footprint and both per capita income and the digitalization index across the panel.

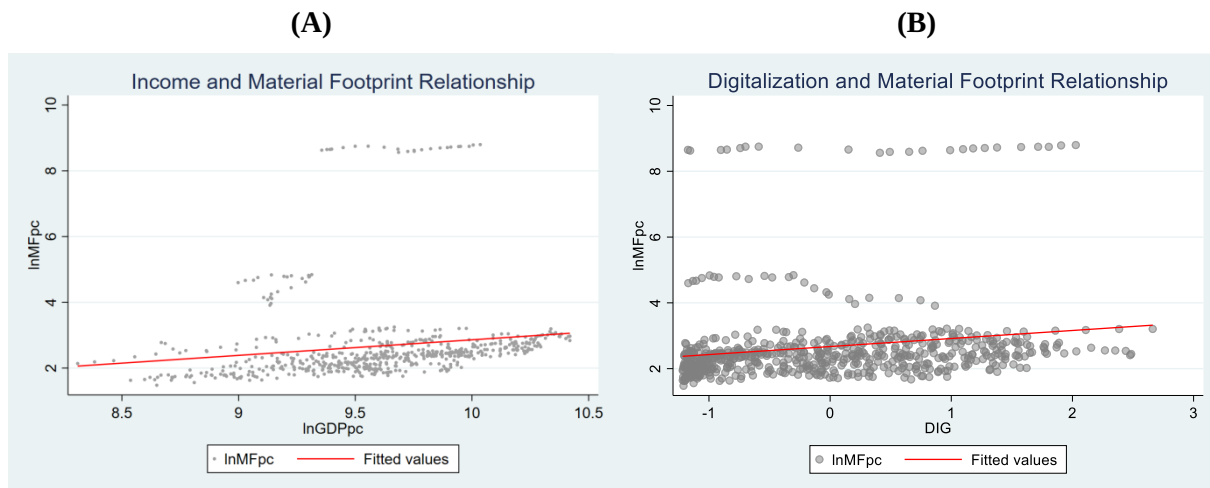


Figure 1: Bivariate Relationships between Key Variables and Material Footprint (2000-2023) (a) Per Capita Income, (b) Digitalization Index

Figure 1 presents scatter plots of the per capita material footprint against two key explanatory variables. Panel (a) demonstrates a positive relationship between per capita income and the material footprint, consistent with the resource-intensive growth trajectory documented for developing countries in the literature. Panel (b) displays a weak and dispersed relationship between the digitalization index and the material footprint at the panel level, which aligns with the insignificant DIG coefficient obtained from the DCCE-MG estimator and reflects considerable heterogeneity across countries. Notably, in both panels, the observations in the upper cluster belong to China.

To assess the potential presence of multicollinearity among the model variables, we conducted a variance inflation factor (VIF) analysis; the results are presented in Table 5.

Table 5: Multicollinearity Test (VIF) Results

Variable	VIF	1/VIF (Tolerance)
lnPOP	3.75	0.266
M2	3.44	0.291
TB	3.26	0.307
IND	3.15	0.318
lnGDPpc	3.02	0.331
TRD	2.43	0.411
DIG	2.29	0.436
ROL	2.19	0.456
URB	1.73	0.578
lnEL	1.55	0.645
Average VIF	2.68	

The VIF values reported in Table 5 range from 1.55 to 3.75. Since these values remain below the commonly used threshold values of 5-10, multicollinearity does not appear to be a serious concern in the model (Çelik, 2020, p. 298). The average VIF is 2.68, and all tolerance values exceed 0.10, supporting this conclusion (Büyüköztürk, 2002; Kalaycı, 2010).

3.2. Cross-section Dependency Tests

In panel data analyses with multiple cross-sections and time dimensions, conducting cross-sectional dependence (CD) analyses is one way to assess whether a shock in one cross-section (for instance, country, city, or firm) would be felt in other cross-sections. Thus, we can determine whether others experience a shock in each cross-section, and the result informs the subsequent steps of the analysis.

We can understand the CD of horizontal slices across the series with the Breusch and Pagan (1980) Lagrange Multiplier (LM) test (CD_{LM1}), the Pesaran (2004) CD test, and the bias-adjusted LM test (LM-adj) developed by Pesaran, Ullah, and Yamagata (2008). The Breusch and Pagan (1980) LM test is recommended when the time dimension is greater than the cross-sectional dimension in the panel ($T > N$). The Pesaran (2004) CD test provides consistent results when the cross-sectional dimension is greater than the time dimension, or when both dimensions are large. When both N and T are large, the bias-adjusted LM test by Pesaran et al. (2008) is applied (Tatoğlu, 2018).

Breusch and Pagan (1980) developed the LM (CD_{LM1}) test statistic, which is a LM test, for examining CD. The LM test can be calculated using the following formula as the starting point:

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it}, i = 1, 2, \dots, N \quad t = 1, 2, \dots, T \quad (2)$$

where i denotes the cross-section dimension, t denotes the time dimension, x_{it} denotes the explanatory variable(s), α_i denotes the constant(s), and β_i denotes the slope coefficients. The LM test statistic is calculated as follows:

$$CD_{LM1} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \quad (3)$$

where, $\hat{\rho}_{ij}^2$: i, j , the correlation test statistic (between the residuals of the i and j units), distributed with $N(N-1)/2$ degrees of freedom χ^2 . This test is applied in the case of $T > N$; however, it can produce inconsistent findings when $N > T$.

Pesaran (2004) proposed the CD test as an alternative to the Breusch-Pagan LM test for examining cross-sectional dependence among residuals, particularly when the cross-sectional dimension is large relative to the time dimension ($N > T$). The Pesaran CD test statistic is expressed as follows:

$$CD_{LM} = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \right) \quad (4)$$

where $\hat{\rho}_{ij}$: i and j indicate the bivariate correlation coefficient between the error terms of the i and j cross-sections. The Breusch-Pagan LM test statistic follows a chi-square distribution with $N(N-1)/2$ degrees of freedom. When N and T are large, or N was large and T was small, the calculation was performed using the formula.

$$CD_{LM2} = \sqrt{\left(\frac{1}{N(N-1)} \right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N (T \hat{\rho}_{ij}^2) \quad (5)$$

Pesaran (2004) mentioned that the CD test statistic asymptotically is from a standard normal distribution ($N(0,1)$) as N and $T \rightarrow \infty$. Monte Carlo simulations indicate that for $N > T$ scenarios, the Pesaran CD test performs more consistently than the Breusch-Pagan LM test (Tatoğlu, 2020, p. 245). Table 6 presents the variable- and model-based CD results.

Table 6: Cross-Section Dependency Results

Variable-based (Pesaran CD)			
Variable	CD Statistic	p-value	Result
lnMFpc	32.21	0.000***	+
lnPOP	26.34	0.000***	+
lnGDPpc	77.58	0.000***	+
DIG	87.33	0.000***	+
lnEL	40.06	0.000***	+
TRD	18.74	0.000***	+
TB	0.22	0.827	-
IND	15.10	0.000***	+
URB	79.83	0.000***	+
ROL	5.29	0.000***	+
M2	52.54	0.000***	+
Model-Based			
Test	Test Statistic	p-value	Result
Breusch-Pagan (1980) LM	$\chi^2 (351) = 1496.161$	0.0000***	+
Pesaran (2004) Scaled LM	2.073	0.0382**	+
Pesaran et al. (2008) Bias-Adjusted LM	0.886	0.0375**	+
Average Absolute Correlation	0.363		

Note: *** and ** indicate significance at the 1% and 5% levels, respectively. (+) indicates the presence of CD; (-) indicates its absence.

The model output, along with the average absolute correlation tests for the interactions between the variables under investigation, is presented in Table 6. Based on Pesaran's (2004) CD test results, all variables except the trade balance (TB) exhibit cross-sectional dependence at the 1% significance level.

The Breusch-Pagan LM, Pesaran scaled LM, and Pesaran bias-adjusted LM tests reject the null hypothesis of cross-sectional independence. These results support the use of second-generation heterogeneous panel methods in the subsequent analysis.

3.3. Unit Root Test

In panel data analysis, testing for a unit root in the series is crucial to prevent spurious regressions. In this study, the Pesaran (2007) CIPS test, a second-generation unit root test that accounts for CD in the data, was employed.

The CIPS test is an extended version of the Im-Pesaran-Shin (IPS) test (Im, Pesaran, & Shin, 2003), which accounts for CD by separately estimating Cross-sectionally Augmented Dickey-Fuller (CADF) regressions for each cross-section. In this test, t-statistics from CADF regressions for each unit are computed, and the CIPS test statistic for the panel is obtained by averaging these statistics across the cross-sections (Pesaran, 2007). The CIPS test statistics for the panel are calculated by taking the average of the CADF t-statistics obtained for each cross-section, as presented in Equations (6) and (7).

$$CIPS(N, T) = \bar{t} = \frac{1}{N} \sum_{i=1}^N t_i(N, T) \quad (6)$$

$$CIPS = N^{-1} \sum_{i=1}^N CADF_i \quad (7)$$

The discrete version of the CIPS statistic is formulated as in Equation 8 (Pesaran, 2007, p. 288).

$$CIPS^*(N, T) = \frac{1}{N} \sum_{i=1}^N t_i^*(N, T) \quad (8)$$

The stationarity properties of the variables were first examined at the level and then in first differences, and the results are presented in Tables 7 and 8, respectively.

Table 7: CIPS Unit Root Test Results (Level)

Variable	Constant Lag = 0	Constant Lag = 1	Constant and Trend Lag = 0	Constant and Trend Lag = 1
lnMFpc	-2.610***	-0.937	-3.047***	-2.969***
lnPOP	3.954	0.147	7.413	3.709
lnGDPpc	1.970	1.894	0.908	-0.510
DIG	1.756	0.551	3.180	2.485
lnEL	-2.337**	-1.981**	0.504	0.877
TRD	2.945	3.625	0.979	1.053
TB	-0.170	-0.874	-0.196	-2.077**
IND	-0.351	0.239	-1.097	-2.436***
URB	3.197	-0.383	5.133	3.638
ROL	-1.130	-2.349***	0.607	-0.681
M2	-3.167***	-1.696**	-1.046	0.740

***, ** indicate significance levels of 1% and 5%, respectively.

Table 8: CIPS Unit Root Test Results (First Difference)

Variable	Constant Lag = 0	Constant Lag = 1	Constant and Trend Lag = 0	Constant and Trend Lag = 1
$\Delta \ln MFpc$	-14.839***	-7.766***	-13.994***	-6.043***
$\Delta \ln POP$	-5.609***	-7.814***	-4.729***	-6.412***
$\Delta \ln GDPpc$	-8.537***	-5.184***	-6.689***	-1.822**
ΔDIG	-9.721***	-5.397***	-10.152***	-7.367***
$\Delta \ln EL$	-14.142***	-7.352***	-12.531***	-5.131***
ΔTRD	-12.602***	-5.908***	-10.790***	-3.696***
ΔTB	-13.335***	-9.695***	-10.954***	-7.406***
ΔIND	-11.881***	-8.925***	-9.466***	-6.345***
ΔURB	-6.422***	-5.876***	-7.756***	-4.971***
ΔROL	-12.698***	-8.150***	-10.946***	-7.267***
$\Delta M2$	-14.864***	-6.801***	-13.201***	-4.941***

***, ** indicate significance levels of 1% and 5%, respectively.

Table 7 reports the CIPS results for the variables' level series. The natural logarithm of the per capita material footprint (lnMFpc) is stationary in several specifications. For TB and IND, the unit-root null is rejected only in the specification including a constant, trend, and one lag, at the 5% and 1% significance levels, respectively. Table 8 shows that the first differences of all variables are stationary across all specifications.

3.4. Delta Test

In panel data analysis, it is important to determine whether the slope coefficients differ across units such as countries. This is significant for deciding which estimation method to use in the next stage and for correctly interpreting the results. Pesaran and Yamagata (2008) used the Delta test that they designed by refining Swamy's (1970) test to check if the slopes are homogeneous in large panels. Swamy's (1970) test was originally designed for panels in which the number of units is small relative to the time dimension, and it permits heteroscedasticity across units. Pesaran and Yamagata (2008) introduced the delta test by refining the Swamy test to make it suitable and efficient for panel data models with both large cross-sectional and time dimensions. The standard delta test statistic for large samples is depicted in Equation 9.

$$\tilde{\Delta} = \sqrt{N} \left(\frac{N^{-1} \tilde{S} - k}{\sqrt{2k}} \right) \quad (9)$$

To raise the power of the test in small samples, Pesaran and Yamagata (2008) developed the adjusted delta ($\tilde{\Delta}_{adj}$) that includes a small sample variance correction, as indicated in Equation 10.

$$\tilde{\Delta}_{adj} = \sqrt{N} \left(\frac{N^{-1} \tilde{S} - k}{\sqrt{\text{Var}(t, k)}} \right) \quad (10)$$

Table 9 presents the outcomes of the Pesaran and Yamagata (2008) Delta test, which was used to check if the slope coefficients are the same for all countries.

Table 9: Delta Test Results

Test	Statistic	p-value
$\tilde{\Delta}$	8.751	0.000***
$\tilde{\Delta}_{adj}$	12.654	0.000***

Note: *** indicates a significance level of 1%.

The results of Pesaran and Yamagata's (2008) delta test, applied to determine whether the slope coefficients are homogeneous across countries, are presented in Table 9. According to the test results, both delta and adjusted delta statistics are statistically significant at the 1% significance level. This finding indicates that the slope coefficients are heterogeneous across countries; i.e., the long-run coefficients differ by country.

3.5. Westerlund Cointegration Test

The stationarity of the first-differenced series necessitated testing for a long-run equilibrium relationship among the variables. Given the presence of cross-sectional dependence and slope heterogeneity, the error-correction-based Westerlund (2007) panel cointegration test, which explicitly accounts for these characteristics, was employed in place of first-generation cointegration tests. The Westerlund test evaluates both panel-level and group-level cointegration relationships. The Westerlund (2007) cointegration test is fundamentally based on the following error correction model:

$$\Delta y_{it} = \delta'_i d_t + \alpha_i (y_{i,t-1} - \beta'_i x_{i,t-1}) + \sum_{j=1}^{pi} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{pi} y_{ij} \Delta x_{i,t-j} + e_{it} \quad (11)$$

Here, the subscripts i and t denote the cross-sectional and time dimensions, respectively; d_t represents the deterministic components; x_{it} stands for the independent variables; and e_{it} is the error term. The equation is then formulated as follows:

$$\Delta y_{it} = \delta'_i d_t + \alpha_i y_{i,t-1} + \lambda'_i x_{i,t-1} + \sum_{j=1}^{pi} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{pi} y_{ij} \Delta x_{i,t-j} + e_{it} \quad (12)$$

In this equation, $\lambda_i' = -\alpha_i \beta_i'$ where the parameter α_i determines the speed of error correction. If $\alpha_i < 0$, the error correction mechanism is operational, indicating that the system is cointegrated. The Westerlund test reports two group-mean statistics (Gt and Ga) and two panel statistics (Pt and Pa), which assess cointegration at the group and panel levels, respectively.

Given the relatively short time dimension of the study ($T = 24$), lag and lead lengths were not incorporated into the test specification. Additionally, robust p-values were obtained via 500 bootstrap iterations to mitigate the distorting effects of cross-sectional dependence.

Table 10: Westerlund Cointegration Test Results

Statistics	Type	Robust P	Conclusion
Gt	Group-Mean	0.026	Evidence for some panel members
Ga	Group-Mean	0.950	Cointegration: NO
Pt	Panel-Wide	0.186	Cointegration: NO
Pa	Panel-Wide	0.742	Cointegration: NO

The bootstrap-robust p-value for the Gt statistic is significant at the 5% level, providing evidence of cointegration for at least some panel members. However, the remaining statistics (Ga, Pt, and Pa) are insignificant, indicating that the results do not support a uniform cointegration relationship across the panel.

3.6. Coefficient Estimator and Quantile Analysis

The Westerlund test provides evidence of cointegration for at least some panel members, although the results are not uniform across the panel. Given the presence of cross-sectional dependence and slope heterogeneity, the DCCE-MG estimator was used to obtain the long-run mean coefficients. In the context of panel data studies, it is important to correct for CD, slope heterogeneity, and unobserved common factors so that long-term coefficients can be reliably estimated. Because the presence of CD and heterogeneity was confirmed by the tests in this study, the DCCE-MG estimator was applied. The DCCE-MG analysis can account for the influence of latent dynamic factors and random shocks by extending the model via cross-sectional means. Moreover, it addresses heterogeneity by allowing individual cross-sectional regressions, thereby enhancing the reliability of the results.

Although the DCCE-MG estimator highlights the average effects over a long period, it cannot depict the influence of the variables at various points (quantiles) in the distribution of the dependent variables. Hence, MM-QR ($\tau = 0.5$) was employed as a complementary estimator to examine the relationships at the conditional median of the dependent variable. The MM-QR handles the variance problem more effectively, makes standard errors more robust, does not require the assumption of normality, is resistant to outliers, and provides reliable results in heterogeneous panels (Machado & Silva, 2019). Therefore, MM-QR was considered suitable as a complementary analytical tool alongside the DCCE-MG results. Furthermore, a 500-replication bootstrap was performed to enhance the study's robustness.

The DCCE-MG and MM-QR (0.5 Quantile-Median) estimation results are displayed in Table 11.

Table 11: Long-Run DCCE-MG Estimates and Bootstrap MM-QR Estimates at the Conditional Median

Variable	DCCE-MG (Coefficient)	DCCE-MG (p- value)	MM-QR (Coefficient)	MM-QR (p- value)
lnPOP	-13.765	0.052*	-0.0638	0.002***
lnGDPpc	-0.196	0.785	0.8226	0.000***
DIG	-0.323	0.155	-0.0687	0.001***
lnEL	-0.158	0.553	0.2334	0.000***
TRD	-0.0077	0.011**	-0.00159	0.008***
TB	-0.0139	0.008***	-0.00890	0.000***
IND	0.018	0.139	-0.00450	0.158
URB	-0.074	0.287	0.00581	0.010***
ROL	-0.098	0.539	-0.1409	0.003***
M2	-0.00281	0.384	0.00650	0.000***
Diagnostic Tests				
CD statistic		-0.44		
CD p-value		0.662		
R ²		0.95		

Note: ***, **, and * indicate significance at the 1 %, 5 %, and 10% levels, respectively. MM-QR results were obtained using a 500-repetition bootstrap method.

The diagnostic statistics in Table 11 indicate that the CD in the model has been almost completely removed and common shocks have been controlled. The high R² value suggests that the estimated coefficients have strong explanatory power for long-term variations.

Trade openness and the trade balance, both included as control variables, have negative and statistically significant coefficients in both estimators. The negative TB coefficient indicates that a higher trade-balance value is associated with a lower material footprint per capita. The channels underlying this relationship are not directly examined in the study. For lnPOP, the DCCE-MG estimate is relatively

large and marginally significant at the 10% level, whereas the MM-QR estimate is smaller and statistically significant at the conditional median. The $\ln\text{POP}$ variable is measured as the natural logarithm of total population. Given the large magnitude and marginal significance of the DCCE-MG coefficient, the result offers only weak evidence and should not be taken to imply that population growth generally reduces the material footprint per capita.

Although the digitalization variable is a negative and insignificant factor in DCCE-MG, it is significant and negatively signed at 1% in MM-QR. The negative and statistically significant MM-QR coefficient suggests that digitalization is associated with a lower material footprint at the conditional median. The rule of law coefficient is also negative and statistically significant only in the MM-QR estimates, indicating a negative association at the conditional median.

In the MM-QR estimates, per capita income, energy intensity, urbanization, and financial depth have positive and statistically significant coefficients at the conditional median. Industrialization is statistically insignificant in both estimators.

Most coefficients are statistically insignificant in the DCCE-MG estimates, whereas several variables are significant only in the MM-QR estimates. As these estimates are conditional-median results, they capture distributional rather than average long-run effects. Accordingly, H1, H2, and H3 are supported only by the MM-QR estimates, while H4 is supported by the differences between the two estimators.

3.6.1. A Comparative Evaluation of DCCE-MG and MM-QR Estimation Results

A comparison of the DCCE-MG and bootstrap MM-QR estimates reveals differences in both significance levels and coefficient magnitudes across the variables. These differences are expected because DCCE-MG estimates long-run mean effects, whereas MM-QR focuses on the conditional median.

Table 12: Comparison of DCCE-MG and MM-QR Estimation Results

Variable	DCCE-MG	MM-QR	Consistency	Interpretation
$\ln\text{POP}$	Negative & significant at 10% ($p=0.052$)	Negative & significant ($p=0.002$)	Partially consistent	Negative in both estimators, with stronger significance in MM-QR
$\ln\text{GDPpc}$	Insignificant ($p=0.785$)	Positive & significant ($p=0.000$)	Divergent	Positive association at the conditional median
DIG	Insignificant ($p=0.155$)	Negative & significant ($p=0.001$)	Divergent	Negative association at the conditional median
$\ln\text{EL}$	Insignificant ($p=0.553$)	Positive & significant ($p=0.000$)	Divergent	Positive association at the conditional median
TRD	Negative & significant ($p=0.011$)	Negative & significant ($p=0.008$)	Consistent	Negative association in both estimators
TB	Negative & significant ($p=0.008$)	Negative & significant ($p=0.000$)	Consistent	Negative association in both estimators
IND	Insignificant ($p=0.139$)	Insignificant ($p=0.158$)	Consistent	Insignificant across both models
URB	Insignificant ($p=0.287$)	Positive & significant ($p=0.010$)	Divergent	Positive association at the conditional median
ROL	Insignificant ($p=0.539$)	Negative & significant ($p=0.003$)	Divergent	Negative association at the conditional median
M2	Insignificant ($p=0.384$)	Positive & significant ($p=0.000$)	Divergent	Positive association at the conditional median

The MM-QR estimates were obtained using 500 bootstrap replications.

Upon examining Table 12, the variables can be categorized into three groups. The first group includes variables that yield consistent results in both estimators: trade openness (TRD) and the trade balance (TB) have negative and statistically significant coefficients, whereas industrialization (IND) is statistically insignificant in both. In the second group, per capita income (lnGDPpc), energy intensity (lnEL), urbanization (URB), and financial depth (M2) are positive and significant only in the MM-QR estimates. Digitalization (DIG) and the rule of law (ROL) are negative and significant only in the MM-QR estimates. The third group consists of the population (lnPOP) variable, which exhibits different levels of significance in the two estimators.

When country-specific effects vary substantially, averaging across countries can conceal relationships that appear at the conditional median.

3.7. Additional Analyses

Model 1 reports the parsimonious specification, which includes population, per capita income, digitalization, the trade balance, and financial development. To examine whether the estimates are sensitive to major common shocks and possible structural changes, three additional specifications were estimated. Model 2 includes dummy variables for the 2008-2009 global financial crisis and the 2020-2021 COVID-19 period. In Model 3, these crisis variables were incorporated through the `globalcr()` specification. Model 4 includes an interaction term between the digitalization index and a post-2015 dummy variable ($DIG_post = DIG \times post2015$) to examine whether the effect of digitalization changed after 2015. The results are presented in Table 13.

Because Table 13 uses a parsimonious specification, its coefficients are not directly comparable with those of the full model in Table 11.

Table 13: Additional Analyses Based on a Parsimonious Specification (DCCE-MG)

Variables	Model 1: Parsimonious Specification (2000-2023)	Model 2: Crisis Dummies	Model 3: <code>globalcr()</code>	Model 4: $DIG \times post2015$
lnPOP	-1.377 (0.389)	-2.135 (0.167)	-2.135 (0.167)	-0.313 (0.840)
lnGDPpc	0.722** (0.012)	0.806*** (0.000)	0.806*** (0.000)	0.547** (0.038)
DIG	0.112 (0.158)	0.109* (0.099)	0.109* (0.099)	0.158* (0.060)
TB	-0.005** (0.005)	-0.007*** (0.000)	-0.007*** (0.000)	-0.005*** (0.000)
M2	0.002 (0.181)	0.001 (0.528)	0.001 (0.528)	0.001 (0.389)
crisis2008	-	0.006 (0.734)	-	-
covid2020	-	0.047 (0.116)	-	-
DIG_post	-	-	-	-0.033 (0.441)
CD statistic	-1.29 (0.197)	-2.51 (0.012)	-2.51 (0.012)	-0.84 (0.401)
R ² (MG)	0.94	0.95	0.95	0.95

Note: Values in parentheses are p-values. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. `post2015` equals 1 for years from 2016 onward, and $DIG_post = DIG \times post2015$. The crisis dummies cover the 2008-2009 and 2020-2021 periods. The CD statistic is based on the Pesaran (2004) CD test.

Table 13 shows that the TB coefficient remains negative and statistically significant in all four specifications, whereas the M2 coefficient remains statistically insignificant. The signs of the other coefficients are generally similar across the models, although their magnitudes and significance levels vary.

In Model 2, the coefficients of the crisis dummy variables are statistically insignificant. This means that the model does not identify an additional statistically significant effect associated with the 2008-2009 financial crisis or the 2020-2021 COVID-19 period. However, the significant CD statistic in Models 2 and 3 indicates that residual cross-sectional dependence is still present, so these results should be interpreted with caution. Model 3 produces results that are close to those of Model 2.

In Model 4, the DIG_post interaction term is statistically insignificant. Therefore, the results do not provide evidence that the coefficient of digitalization changed after 2015. These additional results should be interpreted separately from the full model in Table 11 and do not constitute a direct robustness test of all its coefficients.

4. Conclusion

This study empirically examines the effects of digitalization and financial development on the material footprint in developing countries using an extended STIRPAT framework. The analysis uses DCCE-MG and bootstrap MM-QR for 27 developing countries with complete data for the 2000-2023 period. Because the results differ across countries and estimation methods, the same policy response may not be suitable for all countries. This study seeks to answer the following research question: How do digitalization and financial development affect the material footprint in developing countries, and do these effects differ between the long-run mean and conditional median estimates?

Among the control variables, trade openness and the trade balance have negative and statistically significant coefficients in both estimators. A higher trade-balance value is associated with a lower material footprint per capita. However, the channels underlying this relationship are not directly examined in the study. The fact that the digitalization variable has a negative and significant effect at the median level means that advances in digital access and connectivity may support more efficient resource use in developing countries. Similarly, the negative and statistically significant ROL coefficient in the MM-QR estimates suggests that stronger institutions are associated with a lower material footprint at the conditional median. The results should therefore be interpreted in relation to country-specific conditions rather than generalized to the entire sample.

In the MM-QR estimates, per capita income, energy intensity, urbanization, and financial development have positive and statistically significant coefficients. These findings relate to the conditional median and should not be interpreted as long-run mean effects for the full panel. The negative DCCE-MG population coefficient should be interpreted cautiously and should not be taken as evidence that population growth generally reduces the material footprint per capita. In the parsimonious specifications reported in Table 13, the TB coefficient remains negative and statistically significant, whereas M2, the crisis dummies, and the DIG_post interaction term remain statistically insignificant.

The findings indicate the necessity of environmental policy design in developing countries that considers the heterogeneity and structural differences between countries. Under these circumstances, the key policy areas that should be prioritized are the following: development of digital infrastructure and the use of digital technologies to facilitate the green transition; enhancement of institutional capacity; promotion of technological investments that bring about resource and energy efficiency; and a faster switch to renewable energy. Moreover, changes in financial systems, with green regulations that promote green investments and coherence between trade and sustainability policies, would help stem the material footprint.

This study has a several limitations. The digitalization indicator was constructed from only a few components because of a lack of data. Future work may examine the separate impacts of different aspects of digitalization (e-commerce, digital public services, artificial intelligence, and Industry 4.0 technologies) on the material footprint. Additionally, it would be valuable to examine the role of company structures in environmental performance, circular economy practices, and non-linear impact mechanisms and perform a comparative analysis of high- and low-income countries. The Westerlund test provides mixed evidence of cointegration, as only the Gt statistic is statistically significant. The long-run results should therefore be interpreted with this limitation in mind. Future studies could test the robustness of these results using alternative estimators and cointegration procedures.

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Araştırma Makalesi

Digitalization and Financial Development as Drivers of Material Footprint: Evidence from Developing Countries

*Malzeme Ayak İzinin Belirleyicileri Olarak Dijitalleşme ve Finansal Gelişme:
Gelişmekte Olan Ülkelerden Kanıtlar*

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Genişletilmiş Özet

Sanayi Devrimi'nden sonra hız kazanan üretim ve tüketim faaliyetleri, küresel ekosistem üzerinde daha önce görülmemiş bir baskı yaratmıştır. Günümüzde insanlığın doğal kaynakları kullanım düzeyi, doğanın kendini yenileme kapasitesini aşmış ve bu durum ciddi bir ekolojik dengesizliğe yol açmıştır. Bu gelişmeler, ülkelerin ekonomik büyüme için kullandığı kaynakları, çevresel sürdürülebilirlik çerçevesinde yeniden değerlendirmelerini zorunlu hale getirmektedir. Çevresel bozulmayı ölçmek için kullanılan göstergelerden en yaygın olanlarından biri karbondioksit emisyonlarıdır. Ancak üretim süreçlerinin küreselleşmesi ve tedarik zincirlerinin giderek daha karmaşık hale gelmesi yalnızca üretim temelli emisyon göstergelerinin çevresel etkiyi tam anlamıyla yansıtmada yetersiz kalmasına neden olmaktadır. Bu nedenle biyokütle, fosil yakıtlar, metaller ve metalik olmayan minerallerin toplamını ifade eden malzeme ayak izi, çevresel baskıyı daha kapsamlı biçimde ölçen bir gösterge olarak öne çıkmaktadır.

Çevresel bozulmayı açıklamaya yönelik geliştirilen teorik yaklaşımlar arasında IPAT modeli önemli bir başlangıç noktasıdır. Bununla birlikte, modelin değişkenler arasında doğrudan bir orantı ile ilerlemesi çeşitli eleştirilere neden olmuştur. Bu sınırlılığı gidermek amacıyla geliştirilen STIRPAT modeli ise nüfus, refah ve teknolojinin çevresel etkilerini daha esnek ve doğrusal olmayan bir şekilde analiz etme olanağı sunmaktadır. Özellikle gelişmekte olan ülkeler açısından ekonomik büyüme ile çevresel sürdürülebilirlik arasında bir denge kurma çabası içinde olması bu modelin öne çıkmasını sağlamaktadır. Bu çalışma STIRPAT modelini genişleterek dijitalleşme ve finansal gelişmenin gelişmekte olan ülkelerde malzeme ayak izi üzerindeki etkilerini incelemeyi hedeflemektedir.

Literatür incelendiğinde, dijitalleşme ve finansal gelişme ile çevre arasındaki ilişkiler konusunda farklı görüşlerin bulunduğu görülmektedir. Dijitalleşmenin çevre üzerindeki etkisi genellikle artan enerji talebi ile sağlanan verimlilik üzerinden tartışılmaktadır. Çalışmaların bir kısmı, bilgi ve iletişim teknolojilerinin yaygınlaşmasının veri merkezlerinin artan enerji tüketimi ve elektronik atıklar nedeniyle malzeme ayak izini artırdığını belirtmektedir. Diğer yandan dijitalleşmenin kaynak kullanımını azaltarak üretim süreçlerini daha verimli hale getirdiğini savunan çalışmalar mevcuttur. Benzer bir durum, finansal gelişme için de geçerlidir. Finansal sistemin gelişmesi, firmalara çevre dostu teknolojilere yatırım yapma imkânı sağlayarak olumlu bir etki yaratabilmektedir. Tersine bir şekilde tüketici kredilerinin genişlemesi, enerji yoğun tüketimi teşvik ederek çevresel bozulmayı arttırabilmektedir. Kurumsal kalitenin önemli bir göstergesi olan hukukun üstünlüğü, çevresel düzenlemelerin uygulanmasını destekleyerek çevresel sonuçlar üzerinde olumlu bir rol

oynayabilmektedir. Dijitalleşme ve finansal gelişmenin çevresel etkilerini birlikte ele alan ve malzeme ayak izini odak noktası yapan çalışmalar ise oldukça sınırlıdır. Bu çalışma, gelişmekte olan ülkelere dijitalleşme ve finansal gelişme ile malzeme ayak izi arasındaki ilişkiyi genişletilmiş STIRPAT modeli çerçevesinde incelemektedir.

Bu çalışmada, Dünya Bankası verileri esas alınarak seçilen 27 gelişmekte olan ülkeye ait 2000-2023 dönemini kapsayan yıllık panel veri seti kullanılmıştır. Analizde bağımlı değişken olarak kişi başına düşen malzeme ayak izi kullanılırken açıklayıcı değişkenler olarak toplam nüfus, kişi başına düşen gelir, dijitalleşme endeksi ve para arzı kullanılmıştır. Dijitalleşme endeksi, internet kullanıcıları ve sabit genişbant aboneliklerinden yararlanılarak Z-skoru yöntemiyle oluşturulmuştur. Enerji yoğunluğu, hukukun üstünlüğü, sanayi katma değeri, kentleşme, ticaret açıklığı ve ticaret dengesi ise kontrol değişkenleri olarak modele dâhil edilmiştir. Ekonometrik analiz öncesinde yapılan testler, modelde çoklu doğrusal bağlantı sorunu bulunmadığını göstermiştir. Yatay kesit bağımlılığı testleri, ülkeler arasında güçlü bir etkileşim bulunduğunu ortaya koyarken, ikinci nesil birim kök testleri serilerin birinci farkları alındığında durağan hale geldiğini göstermiştir. Westerlund (2007) testinde yalnızca Gt istatistiği anlamlı bulunmuş; bu nedenle eşbütünleşme kanıtının panelin tamamı için tekdüze olmadığı değerlendirilmiştir. Temel analizde Dinamik Ortak Korelasyonlu Etkiler Ortalama Grubu tahmincisi kullanılmış, koşullu medyan tahminlerini elde etmek amacıyla Momentler Kantil Regresyonu analizinden yararlanılmıştır. Ayrıca kriz kukla değişkenleri ve yapısal kırılma etkileşim terimini içeren ek analizler, daraltılmış bir model üzerinden gerçekleştirilmiştir.

Elde edilen bulgular, değişkenlerin malzeme ayak izi üzerindeki etkilerinin hem ülkeler arasında hem de dağılım düzeyleri açısından farklılık gösterdiğini ortaya koymaktadır. Kontrol değişkenlerinden ticaret açıklığı ve ticaret dengesi, her iki tahminde de negatif ve istatistiksel olarak anlamlıdır. Ticaret dengesi katsayısı, daha düşük bir ticaret açığı veya daha yüksek bir ticaret fazlasının daha düşük kişi başına malzeme ayak iziyle ilişkili olduğunu göstermektedir. Bu ilişkinin altında yatan kanallar ise çalışmada doğrudan incelenmemiştir. STIRPAT literatüründeki genel beklentinin aksine, nüfus katsayısı her iki tahminde negatif bulunmuştur. Ancak DCCE-MG nüfus katsayısının büyüklüğü ve sınırdan anlamlılığı nedeniyle bu bulgu genel bir azaltıcı etki olarak yorumlanmamalıdır. Dijitalleşme ve hukukun üstünlüğü yalnızca MM-QR tahminlerinde negatif ve anlamlıdır. Buna karşılık kişi başına gelir, enerji yoğunluğu, kentleşme ve finansal gelişme yalnızca MM-QR tahminlerinde pozitif ve anlamlıdır. Bu sonuçlar koşullu medyana ilişkin olup panel geneli uzun dönem ortalama etkiler olarak yorumlanmamalıdır. Sanayileşme değişkeni ise istatistiksel olarak anlamlı bir etki ortaya koymamıştır. Daraltılmış modelde ticaret dengesi negatif ve istatistiksel olarak anlamlı kalırken kriz kuklaları ve dijitalleşme etkileşim terimi istatistiksel olarak anlamsız bulunmuştur.

Genel bir değerlendirme yapıldığında, gelişmekte olan ülkelere dijitalleşme ve finansal gelişme ile malzeme ayak izi arasındaki ilişkilerin ülkelere ve kullanılan tahmin yaklaşımına göre farklılık gösterdiği görülmektedir. Bu durum, çevresel sürdürülebilirlik politikalarının tüm ülkeler için tek tip yaklaşımla belirlenmesinin yeterli olmayacağını göstermektedir. Bu bulgular ışığında, gelişmekte olan ülkelere dijital altyapı yatırımlarının artırılması, çevresel düzenlemelerin etkinliğinin güçlendirilmesi, enerji verimliliğini destekleyen teknolojilerin teşvik edilmesi ve yenilenebilir enerjiye geçişin hızlandırılması önem taşımaktadır. Ayrıca finansal sistemlerin çevre dostu yatırımları destekleyecek şekilde yeniden yapılandırılması ve ticaret politikalarının sürdürülebilirlik hedefleriyle uyumlu hale getirilmesi gerekmektedir. Gelecek çalışmalarda farklı dijital teknolojilerin etkileri ayrı ayrı incelenebilir. Ayrıca, Westerlund testinden elde edilen karma bulgular nedeniyle alternatif tahminciler ve eşbütünleşme yöntemleri kullanılabilir.