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Strategic extensions of the STIRPAT model to address environmental footprints: A management perspective on technology and green solutions

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ABSTRACT

This study analyzes data from OECD countries from 1990 to 2020 using an extended Stochastic Impacts by regression on population, affluence, and technology (STIRPAT) model that incorporates green and digital factors alongside urban population, GDP, and environmental technologies. The results show that technological progress, green finance, and green growth reduce ecological footprints, while the digital economy increases them, and digital applications have only a small environmental impact. Quantile-via-moment estimation indicates that the selected variables strongly affect the 90th quantile. These findings suggest that policymakers in OECD countries should prioritize sustainable economic growth and the development of user-friendly digital systems and applications. Promoting green growth and encouraging accessible digital technologies can support sustainable development and create opportunities for innovation across various sectors.

1. Introduction

Globalization has presented opportunities for human progress and heightened potential environmental threats. Instantaneous action must address global greenhouse gas emissions, climate change, deforestation, biodiversity loss, illegal logging, water scarcity and contamination, air and water pollution, waste management, and transportation and production-related hazards. All these factors are given a "Red Light" by the OECD Environmental Outlook 2030, which projects the urgency to address these challenges. Not taking action will result in devastating consequences for our planet and future generations. Additionally, many studies have shown the need to implement new and effective strategies, and there is an increased risk of irreversible damage to our economy and sustainable development (Bansal et al., 2021). It is imperative to note, based on research conducted by Dusenge et al. (2019), that the failure to address carbon dioxide (CO_2) emissions may result in a drastic increase in global average temperatures by 1-3.7 °C by the end of this century. This serious matter requires prompt and effective action to mitigate its impact. Ensuring the coexistence of GDP growth and environmental protection is vital for countries. As per the Outlook report, global GDP is predicted to surge by almost 99% between 2005 and 2030 without any fresh policies. But, without modifying the existing policies, this growth could lead to severe environmental consequences. Hence, implementing effective environmental policies is crucial to achieving mutually beneficial outcomes for the environment, human health, and the economy.

While some countries struggle to decrease their greenhouse gas emissions, progress has been made in separating emissions from economic growth. Unfortunately, global emissions have increased by 1.5 times since 1990, largely due to the use of fossil fuels in developing countries. However, it's important to acknowledge that historically, OECD countries have been responsible for most global emissions. Energy industries in OECD countries are the biggest contributor to GHG emissions at 29%, followed by transport at 24%, manufacturing units at 13%, agriculture with a 9% share, industrial practices at 7%, and waste production at 7%. Despite this, it's heartening to see that OECD countries now contribute only 35% of global CO emissions from energy use, down from over 50% in 1990. The overall trend is determined by CO, which, along with CH and NO, contributes to about 98% of GHG emissions, according to the IEA's report in

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2019. It is crucial to relentlessly advocate for advancing alternative energy sources and strive toward a future where renewable energy plays a more significant role.

The present study delves into four crucial elements that have a foremost impact on ecological footprints: green finance, green growth, digital economy, and digital application. In order to achieve the crucial climate targets, a shift towards a sustainable and resilient global economy is imperative, as pointed out by Ren et al. (2022). The Paris Agreement has garnered support from over 190 countries to restrict global warming to under 2 °C. To realize this goal, it is essential to introduce green finance to expedite the transition towards low-carbon technology and innovative solutions, as highlighted by Sarwar (2019) and Zhou et al. (2019). As noted by Zhou et al. (2020), green finance can effectively balance economic growth and environmental quality, leading to mutually beneficial outcomes. As per the findings of several experts, the adoption of green finance is instrumental in mitigating the dire consequences of environmental pollution and climate change. The second variable examined in the study pertains to "green growth," which encompasses protecting and preserving the environment. As a result, the importance of green growth has gained considerable attention, particularly concerning climate transformation and ecological degradation. Esteemed organizations such as the World Bank, the OECD, and the UNESCAP actively embrace the principles of a green economy (Cao and Bai, 2018). Hussain et al. (2022) and Sarwar et al. (2021) analyzed that there is a relationship between green growth and climate quality. Achieving sustainable development is crucial, and green growth is a key factor in this. It helps promote environmental sustainability while driving economic development.

The importance of digitalization is highlighted in this research, as it has become increasingly valuable in light of resource scarcity and environmental degradation resulting from dependence on fossil fuels. The continuous evolution of computer science and the increasing sophistication of communication technology have opened up possibilities for enhancing energy efficiency and reducing emissions of pollutants. Technological advancements have the potential to offer a significant contribution towards sustainable development. Consequently, a novel type of economy, known as the digital economy, has emerged. Schmidt and Kløverpris (2009) have also looked into the idea of substitution effects, which involve replacing physical goods with virtual ones. Taken together, these findings suggest that technology and digital solutions have great potential to advance sustainability and tackle environmental issues.

This study advances the environmental economics literature by extending the classical Stochastic Impacts by regression on population, affluence, and technology (STIRPAT) framework in two innovative ways. First, it incorporates green finance and green growth simultaneously into the model, enabling a distinction between financial flows explicitly targeted toward sustainability and broader structural shifts in productivity. Prior research has often emphasized either financial development in general or green growth in isolation, but rarely has it evaluated the combined and differentiated impact of these two green drivers within OECD economies (Hussain et al., 2022; Tao et al., 2023). Second, the research introduces the digital economy and digital application as novel proxies of technological progress. While earlier studies have captured the role of digitalization using broad ICT adoption or Internet penetration, this study separates macro-level economic digitalization (industry revenue from information services) from micro-level application intensity (IoT spending). This differentiation matters because it highlights whether environmental benefits stem from structural digital transformation at the industry level or from consumer- and enterprise-level digital tools. Such a distinction has been largely overlooked in OECD-focused work (Meng et al., 2023). Finally, by applying quantile-via-moment estimation alongside heterogeneous panel estimators (AMG, MG, DCCE), the study moves beyond average effects and demonstrates how the significance of green and digital factors varies across different levels of ecological footprint pressure. This methodological contribution provides richer insights for policymakers, showing that interventions are not uniformly effective across the distribution but become most critical at the higher quantiles, where ecological stress is greatest (Chudik and Pesaran, 2015). Together, these contributions provide both conceptual novelty—by integrating green and digital transitions into a unified extended STIRPAT model—and practical relevance, as the results can guide OECD policymakers to prioritize financing mechanisms and digital strategies where they have the strongest marginal impact on reducing ecological footprints.

This researcher in the study has identified three main objectives that measure the ecological footprints of OECD countries. Primarily, the paper provides an in-depth analysis of the STIRPAT (System for Transfer of Pollutants and Analysis of Risk) model that incorporates three variables: Population, affluence, and technology. Furthermore, the model is extended to measure the significance and relationship between green finance and ecological footprints; this can help analyze the correct financing measures to be attained by policymakers. The next objective of the paper is to explore the role of green growth in reducing the ecological footprint. The STIRPAT model is also extended in another way by involving the digital economy and digital applications in this research. The analysis will provide the outcome of an emphasis on digitalization, leading to ecological footprints. The study will employ a quantile methodology to ascertain the optimal level of focus on specific variables in order to enhance environmental standards.

The document is divided into several parts, starting with a thorough literature review. Then, it provides a detailed explanation of the data and variables employed in the paper, which clarifies the methodology utilized. The following sections present the study's findings, accompanied by a comprehensive discussion, and conclude with final recommendations based on the research results.

2. Literature review

The study incorporated the STIRPAT model to measure the relationship between green factors and digitalization with ecological footprints. Several researchers have found the use of the STIRPAT model for environmental footprint analysis (Fan et al., 2006; Zuo et al., 2020). Rasool et al. (2021) found the nexus between carbon emissions and economic growth by using the STIRPAT model, suggesting that economic developmental activities cause major hazards to the atmosphere. Ecological footprints have many major contributing factors, and literature provides context to this study that green factors and digitalization are favorable and sometimes unfavorable to environmental health.

2.1. Green finance and green growth impact the environmental footprints

The evolution of financial systems has been found to have notable implications for greenhouse gas emissions. Diverse research efforts have highlighted both positive and negative outcomes on the environment across various geographic locations. Traditional financial development increases environmental degradation, a rise in credit to the private sector, hence proved by several researchers such as Al-Mulali et al. (2015), Ali et al. (2019), Maji et al. (2017), Sarwar et al. (2022), and Shahbaz et al. (2016). Conversely, Abbasi and Riaz (2016) declared that financial development indicators have no significant long-run relationship with CO_2 emissions. The advancement of green finance involves making credit more accessible to promote a sustainable and eco-friendly environment (Xie et al., 2020). Similarly, Tao et al. (2023) utilized an extended STIRPAT framework to investigate the influence of financial development on carbon emission intensity within OECD countries. The study shows that financial development significantly diminishes carbon intensity in the environment, regardless of the indicators. Recent studies emphasize the nuanced role of green financial systems in mitigating emissions. Tao et al. (2023) highlighted how financial development, when steered by ICT, lowers carbon intensity in OECD countries, while Hussain et al. (2022) demonstrated that green growth activities significantly reduce emissions in high-GDP economies, underscoring policy relevance.

Moreover, only a handful of academic studies have examined the impact of green growth, with all of them treating it as the dependent variable (Tawiah et al., 2021). Similarly, Maiti (2022) used green growth as an independent variable, but in terms of environmental policy strengthening, socio-economic dynamics, and renewable energy utilization, carbon dioxide emissions for 32 countries, and found that environmental-related technology (EO) innovation is increased by environmental policy strengthening (EPS), whereas renewable energy supply (RE) shows no impact on green growth. Moreover, the socio-economic factor has an indirect impact. The study conducted by Hussain et al. (2022) involved a careful selection of twenty high-GDP countries, with data analysis spanning from 2000 to 2020, utilizing advanced econometric methods. The results of their research indicate a negative correlation between emissions and green growth, with green growth activities effectively reducing emissions. The authors employed a cross-sectional autoregressive distributed lag estimator for long and short runs.

2.2. Digital economy and digital application impact on environmental footprints

New research underscores digitalization's dual role in ecological outcomes. Meng et al. (2023) found that the digital economy reduces carbon intensity across 282 Chinese cities, while Zhang et al. (2023) confirmed that structural digital transformation enhances environmental quality. Both studies suggest digitalization can deliver sustainability benefits when strategically directed toward green innovation. Lin and Zhou (2021) used the non-radial distance function (NDDF) to gauge energy and carbon emission performance in the case of China. In their paper, they showed that the Internet development has significantly progressed China's energy and carbon emission performance; therefore, environmentally supportive characteristics. Meng et al. (2023) delivered that the digital economy can significantly reduce carbon intensity, and additional testing by different methods. The conclusion remained effective. Moreover, the study claims that the digital economy can affect carbon emissions by two significant channels: Encouraging industrial structure advancement and the green revolution. Zhang et al. (2023) claimed a negative relationship between the digital economy and environmental health. Zha et al. (2022) used the spatial error model (SEM), spatial Durbin model (SDM), and spatial autoregressive model (SAR) and found a negative relationship between the digital economy index and carbon emission intensity in the case of 26 cities in the Yangtze River Delta urban agglomeration. Plenty of research is in support of digitalization for the sustainable progression of the nations (Anwar et al., 2024; Sarwar et al., 2022).

3. Data and methodology

This study opted for a dataset from the Organization for Economic Co-operation and Development (OECD) countries spanning from 1990 to 2020.

The ecological footprint data were obtained through the Global Footprint Network (GFN), while the data for urban population and economic growth were obtained from WDI. The factors of technology, green growth, and green finance were derived from the OECD, and digitalization data were sourced from Statista. Additional information can be found in Table 1.

Table 1: Variable description

Variable	Code	Definition	Source
Ecological footprint	EFP	Ecological footprint: Per capita consumption	Global footprint network (GFN)
Urban population	Pop	Urban population	WDI
Economic growth	GDP	GDP per capita (constant 2015 US$)	WDI
Environment-related technology	Tech	Environment-related technologies	OECD
Green finance	GF	Renewable energy public RD&D budget (% of total energy public RD&D)	OECD
Green growth	GG	Environmentally adjusted multifactor productivity growth	OECD
Digital economy	DE	Industry revenue of "information service activities" (in million U.S. Dollars)	Statista
Digital application	DA	Retail IoT spending 2013-2018	Statista

3.1. Theoretical reasoning

The impression of human activities on the environment is significant and far-reaching. To analyze the relationship between human actions and the atmosphere, the IPAT accounting model is commonly used. This model was first introduced in the 1970s and is used to evaluate the primary factors that drive anthropogenic environmental impacts. The IPAT model suggests that environmental impacts arise as a result of three key factors: Population, affluence, and technology, which are represented by the acronym I/PAT. It is important to note that assigning blame for environmental impacts to a single factor is not a viable approach. For example, when a country experiences an increase in affluence while population and technology remain constant, it would be inaccurate to attribute the impacts solely to affluence, as changes in population and technology can also have a significant impact on the overall environmental impact (York et al., 2003). To grasp the significance of each driving force (P, A, and T), one must evaluate the potential for change in each of the drivers by assessing their rate and range of impact, given their interconnectedness. The primary objective of STIRPAT is to estimate the impact of driving forces on the environment. In the logarithmic version of STIRPAT, the coefficient of a driving force indicates its elasticity, which reflects the percentage change in environmental impacts resulting from a one percent change in the driving force. The coefficient is termed "ecological elasticity (EE)." When the STIRPAT is correctly specified and estimated, the EE can be understood as the incremental environmental effects of the underlying driving forces. The STIRPAT model has been used in various studies to analyze the dynamics participating in ecological footprint, carbon releases, and energy emissions (York et al., 2003). Unlike IPAT, the STIRPAT model is a stochastic model that is utilized for testing hypotheses rather than being a mathematical equation. The STIRPAT model's specification is:

$$STIRPAT\ Model: I = P \times A \times T$$

where, $I = EF$, $P = UP$, $A = EG$, $T = ET$

$$I_{it} = \varphi_0 P_{it}^{\rho_1} A_{it}^{\rho_2} T_{it}^{\rho_3} \mu_{it} \quad (1)$$

Model 1: focuses on STIRPAT

$$EFP = f\ (Pop, GDP, Tech) \quad (2)$$

$$EFP_{it} = \varphi_0 Pop_{it}^{\rho_1} GDP_{it}^{\rho_2} Tech_{it}^{\rho_3} \mu_{it} \quad (3)$$

$$lnEFP_{it} = \rho_0 + \rho_1 Pop_{it} + \rho_2 GDP_{it} + \rho_3 Tech_{it} + \varepsilon_{it} \quad (4)$$

where, EFP is determined as the ecological footprint, Pop represents the urban population, GDP stands for economic growth, and $Tech$ denotes environmental-related technology. The study extended the STIRPAT model by incorporating green factors such as green growth and green finance. Cao and Bai (2018) analyzed that there is an affiliation between green growth and the ecosystem, and as far as green finance is concerned, it promotes the management of ecological vulnerabilities effectively and equalizes the practice of both economic and ecological sources. Wang and Zhi (2016) also declared that the impact of green finance in alleviating environmental deterioration and abetting the path toward reaching a sustainable environment is vital. Model 2 represents an extended-STIRPAT model with green factors:

Model 2: focuses on STIRPAT, including Green Factors

$$EFP = f\ (Pop, GDP, Tech, GF, GG) \quad (5)$$

$$EFP_{it} = \varphi_0 Pop_{it}^{\rho_1} GDP_{it}^{\rho_2} Tech_{it}^{\rho_3} GF_{it}^{\rho_4} GG_{it}^{\rho_5} \mu_{it} \quad (6)$$

$$lnEFP_{it} = \rho_0 + \rho_1 Pop_{it} + \rho_2 GDP_{it} + \rho_3 Tech_{it} + \rho_4 GF_{it} + \rho_5 GG_{it} + \varepsilon_{it} \quad (7)$$

where, GF represents green finance proxies by renewable energy public RD&D budget (% of total energy public RD&D), referred to by Khan et al. (2022a). Some researchers have used different measures of green finance. For example, Guo et al. (2022) used green financial indicators such as green credit, green investment, green support, and green insurance. Wang and Ma (2022) applied a composite green finance index, while Meo and Abd Karim (2022) used green bonds as a proxy for green finance. However, these measures focus mainly on financing activities for businesses and do not clearly show the level of actual investment in renewable energy projects. In Model 2, GG represents green growth measured as environmentally adjusted multifactor productivity growth referred to by Hao et al. (2021) and Hussain et al. (2022).

Model 3: focuses on STIRPAT, including Digitalization

$$EFP = f\ (Pop, GDP, Tech, DE, DA) \tag{8}$$
$$EFP_{it} = \varphi_0 Pop_{it}^{\rho_1} GDP_{it}^{\rho_2} Tech_{it}^{\rho_3} DE_{it}^{\rho_4} DA_{it}^{\rho_5} \mu_{it} \tag{9}$$
$$lnEFP_{it} = \rho_0 + \rho_1 Pop_{it} + \rho_2 GDP_{it} + \rho_3 Tech_{it} + \rho_4 DE_{it} + \rho_5 DA_{it} + \varepsilon_{it} \tag{10}$$

The study focuses further on digitalization and has extended the model further by adding more variables, such as the digital economy and digital applications. According to the theory of ecological transformation, digital technologies can improve environmental complications, which provides a hypothetical basis for scrutinizing the role of the expansion of the digital economy in upgrading environmental pollution. Hence, the study incorporated variables in Model 3, such as DE representing digital economy proxies by Industry revenue of "information service activities" (in million U.S. Dollars) and DA denoting digital application proxies as Retail IoT spending 2013-2018.

3.2. Justification of proxies

The choice of proxies is guided by both theoretical foundations and empirical precedent. For the digital economy, industry revenue from information service activities is employed as it reflects the structural integration of digital technologies into national economic systems. This proxy captures the economic weight of digital industries, which theory suggests has direct implications for energy efficiency, industrial upgrading, and green innovation (Meng et al., 2023; Yu et al., 2018). Previous studies have shown that economies with stronger digital sectors benefit from optimized resource allocation and cleaner production, thereby reducing environmental pressures (Lin and Zhou, 2021; Zhang et al., 2023). Unlike narrow measures such as Internet penetration, which only capture access, industry-level digital revenues signal the broader transformation of production and service models, making it a theoretically consistent and policy-relevant indicator. For the digital application proxy, retail IoT spending is chosen to reflect the adoption and diffusion of application-level digital tools. This measure is consistent with arguments in ecological modernization theory, which emphasize that environmental benefits arise not only from macroeconomic structural changes but also from micro-level applications that reshape consumption, logistics, and energy management (Lin and Zhou, 2021; Zhang et al., 2023). IoT technologies in particular have been associated with efficiency gains in sectors such as transport, supply chains, and energy distribution, reducing per-unit emissions and resource use (Higón et al., 2017; Ozcan and Apergis, 2018). By using IoT expenditure as a proxy, the analysis captures the tangible, application-driven dimension of digitalization rather than treating digitalization as an abstract construct. This proxy also differentiates the study from earlier OECD analyses that focus narrowly on aggregate ICT access or e-commerce indicators, thus offering a novel and theoretically grounded approach.

Together, these proxies align with the extended STIRPAT framework by distinguishing between structural and application-level digital transformations. This dual lens allows for a more nuanced analysis of how digitalization interacts with ecological footprints, clarifying whether environmental benefits are driven by sector-wide economic shifts or by specific technological applications at the user and enterprise level.

3.3. Econometrics methods

After establishing the long-term co-integration of selected variables, the next technique is to inspect the extent of the variables. Numerous studies have claimed to profess that cross-sectional dependency befalls nations due to economic shocks and unnoticed components such as globalization. To recognize the foremost consequences of this study, the augmented mean group (AMG), mean group (MG) introduced by Pesaran et al. (1999), and the dynamic common correlated effect (DCCE) technique developed by Chudik and Pesaran (2015) have been applied. The approach of the DCCE is able to contentedly pack through contemplating heterogeneous slopes in which the limits diverge via cross-sections, heterogeneity, and CSD problems in consequence. The study used the non-causality test by Dumitrescu and Hurlin (2012) for handling the heterogeneous panels and cross-dependency. This method can be transcribed as:

$$Y_{it} = \vartheta_i + \sum_{j=1}^{J} \varphi_i^J X_{i(t-1)} + \sum_{j=1}^{J} \mu_i^J Y_{i(t-J)} + \epsilon_{it} \tag{11}$$

where, φ_i^J and μ_i^J signify the coefficient of the estimator, which varies transversely in all nations. Y and X gauge the causality. The D-H causality test presented in Eq. 12 to Eq. 14:

$$H_o = \alpha_o = 0\ for\ \vartheta_i \tag{12}$$
$$H_1: (\alpha_i\ = 0 for\ all\ i = 1,2,3 \ldots \ldots \ldots . N_i) \tag{13}$$
$$H_1: (\alpha_i\ = 0 for\ all\ i = N + 1,2,3 \ldots \ldots \ldots . N_i) \tag{14}$$

where, H_o and H_1 symbolize the null and substitute hypothesis, correspondingly.

4. Results

4.1. Descriptive statistics

Table 2 represents the descriptive statistics of the selected variables. The statistics show that GDP and digital application indicators have the highest means, with 13.144 and 13.442 values, respectively. Moreover, the digital economy and digital application variables have the least standard deviation, showing less deviation as compared to other variables' data.

In a later stage, the study applied the cross-sectional dependence test.

Table 2: Descriptive statistics

	EFP	Pop	GDP	Tech	GF	GG	DE	DA
Mean	11.886	9.314	13.144	11.814	11.272	11.796	11.314	13.442
Median	11.905	9.299	13.185	11.878	11.309	11.733	11.296	13.474
Maximum	12.200	9.580	13.237	11.965	11.629	12.105	11.436	13.525
Minimum	11.636	8.994	12.990	11.583	10.765	11.532	11.211	13.274
Standard deviation	0.124	0.166	0.086	0.117	0.255	0.163	0.057	0.071
Skewness	0.283	-0.113	-0.735	-0.501	-0.540	0.422	0.574	-1.139
Kurtosis	3.066	1.994	1.993	1.684	2.328	1.994	2.665	3.085
Jarque-Bera	0.432	1.417	4.236	3.649	2.158	2.298	1.906	6.928
Probability	0.806	0.492	0.120	0.161	0.340	0.317	0.386	0.031

4.2. Cross-sectional dependence

Table 3 depicts the outcomes of cross-sectional dependence by applying Pesaran's CD, Bias-corrected LM, and Pesaran scaled LM. The results illustrate that all variables are significant and demonstrate the existence of cross-sectional dependency; therefore, it is favorable to apply the first-generation unit root test. The next phase is to employ a homogeneity test to check whether the coefficients are homogeneous.

Table 3: Cross-sectional dependence (CDS tests)

Variables	Pesaran's CD	Bias-corrected LM	Pesaran scaled LM
EFP	26.183***	32.740***	29.466***
Pop	41.324***	60.451***	52.016***
GDP	63.485***	53.163***	58.352***
Tech	97.473***	84.867***	81.897***
GF	28.040***	95.429***	107.391***
GG	30.484***	32.233***	38.805***
DE	63.674***	74.256***	94.348***
DA	45.526***	39.154***	46.903***

***: The level of significance at 1%

4.3. Homogeneity test

To check the homogeneity test, the null hypothesis is that all coefficients are homogeneous, but the results reveal that values are significant at 1% for all the models of the study, as mentioned in Table 4. Therefore, models consist of heterogeneity. In case of the presence of such heterogeneity, it's suitable to relate the mean group form of estimations.

4.4. Unit root test

The presence of a unit root in the generation was evaluated using the Augmented Dickey-Fuller (CADF) tests. It was found that the variables were significant at first difference. To ensure accuracy, it is recommended to use the mean group and pooled mean group tests. According to Table 5, all variables are significant at the 1st difference in both CIPS and CADF tests.

Table 4: Homogeneity test for studied models

	Model 1		Model 2		Model 3	
	Δ	Adj Δ	Δ	Δ Adj Δ	Δ	Adj Δ
EFP	11.492***	18.730***	62.835***	43.185***	38.281***	47.902***
Pop	21.363***	34.193***	42.408***	46.404***	47.040***	19.378***
GDP	17.610***	19.694***	39.285***	30.109***	31.543***	56.306***
Tech	19.105***	26.101***	31.763***	29.487***	45.021***	49.253***
GF			23.580***	19.182***		
GG			17.898***	15.370***		
DE					34.687***	19.362***
DA					18.496***	36.470***

***: The level of significance at 1%

Table 5: Unit root test

Unit root tests	CIPS 1st diff.	CADF 1st diff.
EFP	-8.461***	-6.372***
Pop	-9.585**	-8.055***
GDP	-9.103***	-6.360***
Tech	-6.837***	-9.477***
GF	-6.478***	-6.193***
GG	-7.124**	-5.650***
DE	-10.461*	-7.372***
DA	-7.536***	-5.421***

***: The level of significance at 1%

4.5. Cointegration test

At this stage, it's important to examine whether there's a lasting connection between the independent and dependent variables. For this purpose, we'll need to conduct co-integration tests. To account for cross-sectional dependency, it's advisable to utilize the Westerlund co-integration test. The test results are presented in Table 6, which confirms the existence of a long-term relationship. Additionally, it suggests the possibility of a short-term relationship. For a comprehensive study, we must assess both the long-term and short-term relationships for all three models.

4.6. PMG-ARDL estimation

4.6.1. STIRPAT results interpretation

Based on the findings presented in Table 7, it can be deduced that there exists a positive correlation between the population and ecological footprints in the study area. Specifically, the results indicate that population density has a significant impact on environmental health at a 5% level. This implies that as the population increases in the region, there is a higher likelihood of carbon emissions. The results are in correspondence with Meng et al. (2023), proving a positive and significant relationship, and in contrast to Lin and Zhou (2021), which showed no relationship between population and carbon emissions. The second variable, GDP, which represents economic growth, has the highest coefficient of 2.041 at a 5% significance level, and it has a significant impact on environmental footprints. Essentially, this means that more economic development activities in the region lead to higher hazardous emissions. The study attains similar results to those attained by Tran (2022) and Zha et al. (2022), as opposed to the results by Khan et al. (2022a), which showed a negative relationship among variables. Finally, the third variable of the STIRPAT model establishes that technological factors also influence ecological footprints. Interestingly, the results reveal a negative relationship between technological advancement and ecological footprints. Specifically, the empirical outcomes indicate that TECH has a -1.317 coefficient at a 5% significance level. This implies that countries with more technological development activities tend to reduce carbon emissions and pollutants in the atmosphere. In contrast to the results (Zha et al., 2022), the view is that technological advancement is positively related to carbon emissions. However, many studies prove that technological advancement does strengthen the ability to alleviate carbon emissions, in the case of Pakistan. Chen and Lee (2020) validated that technological innovation has no remarkable effect on environmental quality.

Table 6: Westerlund cointegration

Statistics	Model 1	Model 2	Model 3
Gr	0.007***	0.000***	0.000***
Ga	0.080*	0.002***	0.000**
Pr	0.004***	0.016**	0.052**
Pa	0.024**	0.021**	0.000***

***, **, *: Represents the level of significance at 1%, 5%, and 10%, respectively; Gr and Ga are group statistics; Pr and Pa are panel statistics; Lower values indicate cointegration

Table 7: PMG-ARDL estimation

Variables	Model 1	Model 2	Model 3
Pop	1.528**	3.002***	2.378**
GDP	2401**	0.143***	2.484**
Tech	-1.317**	-1.837**	-1.389*
GF		-2.629***	
GG		-0.714	
DE			-0.291**
DA			3.183
Constant	11.367***	17.253***	8.477***

***, **, *: Represents the level of significance at 1%, 5%, and 10%, respectively

4.6.2. Green factors interpretation

The findings of Model 2 demonstrate a clear correlation between population density and environmental footprints, as well as between GDP and carbon emissions. This indicates that as population density and GDP increase, so does the associated impact on the environment. These results offer valuable insights into the complex relationship between human activity and environmental sustainability. However, when it comes to the variable TECH, it displays a negative correlation with ecological footprints, and incorporating green factors doesn't seem to change its significance. Töbelmann and Wendler (2020) indicated that environmentally friendly technological advancements lead to a significant reduction in CO_2 emissions. On the other hand, universal innovation does not have the same positive impact on the environment. This highlights the urgent need for prioritizing eco-friendly technological advancements to combat the growing threat of climate change. It's worth noting that green finance is crucial in OECD countries, as it exhibits a negative correlation with ecological footprints at a significance level of 1%. This negative association between green finance and ecological footprints is confirmed by Meo and Abd Karim (2022). This underscores the importance of green financing for keeping the environment healthy. On the other hand, green growth doesn't seem to have a significant impact on ecological footprints in OECD countries. The study by Hussain et al. (2022) depicted negative and significant relationships between high-GDP countries and G7 countries, respectively.

4.6.3. Digital factors interpretation

Based on the results of the study, it has been observed that the digital economy exhibits a negative correlation with ecological footprint. This means that the higher the digital economy, the lower the ecological footprint. Meng et al. (2023) corroborated these results, but Wu et al. (2021) substantiated an inverted U-shaped relationship between the digital economy and carbon emissions. On the other hand, it was found that digital applications do not have a significant impact on ecological footprints. Rodríguez et al. (2018) revealed that the residual growth of pollution-adjusted GDP cannot be elucidated by the progress of the environmentally adjusted multifactor productivity growth. According to a study conducted by Shvakov and Petrova (2020), the top 10 digital economies do not experience reduced emissions due to digitalization. In fact, to achieve sustainable development goals, digitalization should be minimized. The study found a clear inverse relationship between digitalization and environmental quality. In addition, the study also revealed that GDP and population have a direct association with carbon footprints. This implies that as GDP and population increase, so does the carbon footprint. The data indicate that technology exhibits a negative correlation with ecological footprints across all three models. These findings provide valuable insights into the impact of the digital economy and technological advancement on the environment, which can aid in the development of sustainable policies and practices.

According to the quantile-via-moment estimation in Table 8, it appears that the variables are not significant at the 10th quantile. This suggests that the government needs to pay more attention to these variables to bring about ecological changes. However, as we move up to the 25th and 50th quantiles, we see that population and GDP have a significant impact on the ecological footprint. This implies that as population and GDP increase, the quality of the environment decreases. It is important for us to take note of these findings and work towards creating a sustainable environment for ourselves and future generations. It is important to note that technology, green finance, green growth, and the digital economy have a significant impact on ecological footprints at higher quantiles (specifically at the 75th and 90th). Therefore, countries should prioritize these factors to make a meaningful impact on the environment. Conversely, the study found that digital applications have an insignificant impact on the environment in higher quantities. These findings can guide policymakers in prioritizing their efforts toward achieving ecological sustainability.

Table 8: Quantile-via-moment estimation

Quantile	10th Quantile	25th Quantile	50th Quantile	75th Quantile	90th Quantile	Scale	Log
			Model 1				
Pop	0.690	0.541**	0.421**	0.313*	0.149*	-0.135*	0.448*
GDP	0.066	0.113*	0.150***	0.184***	0.235***	0.042*	0.142**
Tech	-0.240	-0.160	-0.095	-0.037**	-0.052**	0.073*	-0.110**
Constant	13.389***	14.718***	15.792***	16.751***	18.220***	1.204**	15.543**
			Model 2				
Pop	0.665	0.540*	0.412*	0.306*	0.126*	0.180**	0.450*
GDP	0.071	0.107**	0.145**	0.176**	0.229***	0.041**	0.136**
Tech	-0.188	-0.121	-0.052	-0.074**	-0.100**	0.074**	-0.073**
GF	0.022	0.023	-0.024	-0.025**	-0.035***	0.001**	0.023***
GG	-0.012	0.008	0.029	0.046	-0.075**	0.022	0.023*
Constant	13.750***	14.788***	15.857***	16.734***	18.233***	1.160***	15.540**
			Model 3				
Pop	0.649	0.516*	0.400*	0.285*	0.156*	-0.137	0.428*
GDP	0.073	0.113*	0.148***	0.183***	0.223***	0.042*	0.140**
Tech	-0.200	-0.124	-0.058	-0.008**	-0.082***	0.079**	-0.074**
DE	0.013	0.015	-0.016	-0.018**	-0.029**	0.002*	0.016**
DA	0.063	0.055	0.048	0.041	0.033	-0.008	0.050
Constant	13.028***	14.307***	15.415***	16.517***	17.764***	1.320**	15.144***

***, **, *: Represents the level of significance at 1%, 5%, and 10%, respectively

4.7. Robustness analysis

In order to check the robustness of our results, we have used the MG test as well to validate the PMG test results. Results are reported in Table 9. The MG-ARDL results confirm robustness. Population and GDP remain positively associated with ecological footprints, reinforcing structural drivers. Technology consistently shows a negative impact, validating its mitigating role. Green finance significantly reduces footprints, while green growth is insignificant. The digital economy lowers environmental pressure, but digital applications lack consistent explanatory power across models.

5. Discussion

5.1. STIRPAT factors

The empirical findings support the previous literature and show that population and GDP are contributing factors to ecological footprints. The population consumes energy in the form of electricity, which is generated by non-renewable energy sources, ultimately leading to carbon emissions. Studies support that electricity generation increases energy consumption, such as Keshavarzian and Tabatabaienasab (2022). Hence, transportation increases carbon emissions in the environment, as stated by Adams et al. (2020). Research indicates that there is a positive correlation between economic growth and heightened carbon emissions. This is due to the fact that gross domestic product (GDP) encompasses a wide range of activities that necessitate energy consumption, including the manufacturing and export of goods, transportation, trade, industrialization, infrastructure development, and technological progress. Onofrei et al. (2022) declared that GDP and carbon emissions go hand in hand. Khan et al. (2022b) reported that industrialization and trade affect environmental outcomes. Iqbal et al. (2021) found that export diversification and fiscal decentralization also play a role. Yang et al. (2021) highlighted the contribution of manufacturing growth, while Churchill et al. (2021) showed that transport infrastructure has a negative impact on the environment in OECD countries. The empirical findings in the study elaborate that technology is an important factor in reducing ecological factors. New technologies introduced in OECD countries accommodate low carbon usage, hence reducing the carbon intensity in the air. According to Shi et al. (2021), the intensity of low-carbon technology has consistently increased in OECD countries since 1990, with the chemical industry having the highest level of adoption. In most countries, low-carbon technology is most strongly implemented in the production processes.

The strong effect of technology reflects its direct substitution role: innovations in clean energy and process efficiency immediately displace carbon-intensive practices, while population and GDP remain structural forces whose influence cannot be offset quickly. This explains why GDP and population retain significance across models, whereas technological improvements consistently lower ecological footprints.

Table 9: MG-ARDL estimation

Variables	Model 1	Model 2	Model 3
Pop	0.982***	2.538**	1.364***
GDP	1.534**	1.263***	0.961**
Tech	-0.825**	-2.176***	-2.465**
GF		-1.375***	
GG		-0.514	
DE			-1.327**
DA			2,354
Constant	13.511***	16.048***	11.735***

***, **, *: Represents the level of significance at 1%, 5%, and 10%, respectively

5.2. Green factors discussion

In the study, two crucial factors have been identified and analyzed: Green finance and green growth. Green finance plays a pivotal role in promoting and supporting ecologically sustainable economic activities. By facilitating the development of greener infrastructure, construction, production, and supply chain, it accelerates the shift towards a more sustainable future. It is encouraging to note that OECD countries have made significant strides towards achieving sustainable goals, with green finance being a crucial enabler in this regard. Wang and Zhi (2016) proposed that environmental sustainability can be attained through emerging financing for solar energy projects. Sustainable finance/ green finance inspires investment in novel technologies and R&D, comprising renewable energy. OECD countries with significant negative impacts demonstrate that these countries should increase more involvement in green finance activities in order to reduce ecological footprints. The second variable, green growth, has no impact on ecological footprints in the case of OECD countries. Green growth is predominantly essential for attaining sustainable development as it increases the probability of addressing both ecological sustainability and economic expansion. However, as per the results, the insignificance shows that the government is not taking appropriate measures towards this particular variable for environmental quality. The green manufacturing of goods in OECD countries is shifting to non-OECD countries due to dirty production. But still, OECD countries are net traders of the ecological footprints exemplified in imported goods. Moreover, the net import of such products is the least and cannot be related to eco-friendly production activity. The same results are shown by the quantile approach, but green growth is significant at the 90th percentile rather than green finance at the 75th quantile. This proves that green growth requires more emphasis in this scenario to achieve favorable outcomes. The insignificance of green growth in most estimates suggests that structural productivity improvements alone do not automatically translate into ecological benefits. Without targeted regulations, green growth indicators may reflect efficiency gains that are offset by higher overall production volumes. In contrast, green finance exerts a measurable influence because it channels resources directly toward renewable energy and low-carbon technologies.

5.3. Digital factors discussion

According to the results, the digital economy helps lessen the ecological footprint in the case of OECD countries. The advancement of digital technology has facilitated greater access to inclusive sponsorship, thereby enabling economic agents to benefit from timely and appropriate financial support. Such support can be instrumental in providing enterprises with research and development funds, as well as production and operation support from the supply side. This, in turn, can enhance production efficiency and foster the gradual replacement of fossil fuels with clean energy, resulting in a significant reduction in carbon emissions and promoting green and sustainable development The digital economy has become an essential driver of industrial development, Yu et al. (2018) stated that digitalization offers significant opportunities for optimizing regional resource utilization, reducing energy consumption per unit product, and ultimately, decreasing carbon emissions per unit product. Such advancements are crucial in promoting sustainable practices and facilitating the transition to a low-carbon economy, which is vital for achieving the long-term goals of environmental protection and economic growth. Digital application has no impact on ecological footprints in the case of OECD countries. Though the Internet of Things (IoT) is habitually observed as environmentally destructive because the devices and servers necessitate large amounts of energy, it also grants new opportunities to unravel ecological complications. A few cities have started to use smart streetlights for the purpose of digital applications. The additional potential application could be to aid in contesting deforestation and illegal fishing, as blockchain makes it easier to maintain supply chain transparency, as all contributors have a print of all dealings. AI could identify oil spills in oceans and improve emergency decision support systems using satellite images, but OECD countries' lack of these particular digital applications has not yet been productive for the atmosphere. The divergence between the digital economy and digital applications highlights the difference between systemic digital transformation and fragmented tool adoption. While industry-level digitalization reshapes entire sectors and leads to efficiency gains, isolated IoT spending does not create sufficient scale to influence ecological outcomes. This distinction explains why the digital economy is significant, while digital applications remain statistically weak.

6. Conclusion

In this research, the dataset for OECD countries has been selected, and the AMG, MG, and DCCE techniques have been used. The study uses the STIRPAT model to measure the relationship between ecological footprints, green factors, and digital factors. Green factors are divided into green growth and green finance, while digital factors are divided into digital applications and digital economy. The study finds that GDP and population are directly related to ecological footprints, while technology is indirectly related. Green finance has a negative relationship with ecological footprints, while green growth has no significant impact. Similarly, the digital economy is negatively related to ecological footprints, but digital application has no significant impact on environmental quality.

OECD countries should prioritize green growth and digital applications. Suggestions include boosting green proficiency investment, eliminating harmful policies like non-renewable subsidies, improving macroeconomic governance for sustainability, implementing resource exploitation charges, and urging high-level leadership to support green growth. It is recommended that OECD countries allocate more funds towards research and development in order to facilitate the advancement of digital transformation. This entails a focus on developing user-friendly digital systems, significantly increasing investment in the Internet of Things to realize digitalization targets, bolstering cybersecurity measures to instill greater trust and confidence amongst customers, and effectively leveraging the potential of artificial intelligence to drive enhanced productivity outcomes for businesses.

The study can be extended further by comparing the individual OECD countries to enhance the literature further and provide knowledge about different countries' strategies and emphasis. In addition, research can further be extended by incorporating variables such as digital innovation and research and development, environmental taxes, e-commerce activities, agricultural emissions, and forestry. Moreover, the research can be categorized by different sectors.

List of abbreviations

AMG	Augmented mean group
ARDL	Autoregressive distributed lag
CADF	Cross-sectionally augmented Dickey–Fuller test
CD	Cross-sectional dependence
CIPS	Cross-sectionally augmented IPS (Im–Pesaran–Shin) test
CO_2	Carbon dioxide
DA	Digital application
DE	Digital economy
DCCE	Dynamic common correlated effects
EE	Ecological elasticity
EO	Environmental-related technology
EFP	Ecological footprint
EPS	Environmental policy strengthening
GF	Green finance
GFN	Global footprint network
GG	Green growth
GDP	Gross domestic product per capita
ICT	Information and communication technology
ImPACT	Impact model extension of IPAT
IoT	Internet of Things
IPAT	Impact = population × affluence × technology
LM	Lagrange multiplier
MG	Mean group
MG-ARDL	Mean group–autoregressive distributed lag
OECD	Organization for Economic Co-operation and Development
Pop	Urban population
R&D	Research and development
RD&D	Research, development, and demonstration

RE	Renewable energy
SAR	Spatial autoregressive model
SDM	Spatial Durbin model
SEM	Spatial error model
STIRPAT	Stochastic impacts by regression on population, affluence, and technology
UNESCAP	United Nations Economic and Social Commission for Asia and the Pacific
VAR	Vector autoregression
WDI	World development indicators

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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