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ORIGINAL ARTICLE OPEN ACCESS

FinTech, Financial Inclusion, and Environmental Outcomes: Evidence From the European Transition Towards Sustainability

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ABSTRACT

This paper aims to investigate Europe's transition towards sustainability. We explore the role of FinTech, financial inclusion, green innovation, renewable energy, and natural resource rents on carbon dioxide emissions, greenhouse gas emissions, and the ecological footprint. This paper applies a panel dataset of 31 European countries from 2004 to 2021. The analysis is based on the Panel Corrected Standard Error estimation followed by the Driscoll–Kraay standard errors method and Feasible Generalized Least Squares method. The results demonstrate that FinTech, financial inclusion, and renewable energy considerably lessen emissions and ecological footprint. It ends with policy issues to promote sustainable development targets in Europe.

1 | Introduction

Climate change and environmental deterioration continue to be major worldwide issues, with Europe among the most vulnerable regions. Rising temperatures, droughts, and changing rainfall patterns are harming ecosystems and communities (Obobisa and Ahakwa 2024). According to a report by the European State of the Climate (2024), Europe experienced climate divide and extensive floods in 2024, making it the continent with the highest rate of warming. Today, almost 80% of the world's population resides in nations that are beyond their ecological capacity, with an average ecological footprint in Europe reaching 4.90 global hectares per person in 2020, which is almost double the global average of 2.47 (GFN, 2022).[1] Despite determined EU policies like the European Green Deal[2] (2020), Fit for 55 plan[3] (2021), and REPowerEU[4] in 2022, Europe still accounts for approximately 8% of global energy-related emissions. This disparity emphasizes the urgency to find additional sustainability drivers, beyond conventional governmental initiatives.

At a theoretical level, FinTech offers different prospects for environmental outcomes. It can serve as a dematerializer by minimizing resource consumption through the substitution of paper-based systems, facilitating remote transactions, and enhancing efficiency in financial services (Wang et al. 2023). Innovations such as mobile payments, digital loans, and online investing platforms can enhance accessibility while reducing the environmental impact of financial intermediation (Yao and Yang 2025; Bian et al. 2024). On the other hand, FinTech may act as a rebound amplifier, as digitalization and technologies like blockchain elevate electricity consumption and increase the environmental costs associated with data-driven financial systems (Liu 2025; Hou et al. 2024). This indicates that the overall impact of FinTech on the environment remains unclear.

Financial Inclusion (FI) covers another significant aspect of digital finance. It refers to the capacity of firms and individuals to access affordable financial services such as insurance, credit, savings and payment systems (Tchidi and Zhang 2024; Demir et al. 2022). Together, FinTech and FI expand access to financial products to reach underbanked groups in society, particularly rural or low-income people, by reducing cost, distance, and documentation barriers via peer-to-peer lending platforms, mobile banking, and digital payments (Tchidi and Zhang 2024; Demir et al. 2022). These systems also help achieve

sustainability goals by facilitating access to green financial tools, enhancing transparency, and allocating funds to low-carbon initiatives (Yao and Yang 2025).

A similar line of analysis underlines the significance of financial intermediation in facilitating green investment. Financial systems channel resources into renewable energy, sustainable infrastructure, and low-carbon technologies, while FI guarantees that families and businesses may obtain credit and savings to implement cleaner alternatives (Tchidi and Zhang 2024; Demir et al. 2022). Access to economic financial services facilitates the dissemination of green technologies and supports long-term environmental objectives (Ghouse et al. 2025; Umar and Safi 2023). Therefore, be it through FinTech, conventional intermediation, or inclusive access, finance in various forms can serve as a critical mechanism in promoting ecological sustainability.

The empirical evidence, nonetheless, remains mixed. Gao et al. (2024) finds that FinTech lowers carbon emissions and enhances environmental quality by supporting forestation projects, while Ghouse et al. 2025) reveals how FI significantly impacts ecological sustainability. Umar and Safi (2023) show that green innovation lowers carbon emissions in OECD countries. At the same time, other studies reveal that FinTech may increase emissions through elevated energy consumption resulting from higher electricity demand, particularly for blockchain-based activities (Liu 2025; Hou et al. 2024). Also, weak regulatory systems can limit the environmental benefits of digital finance, leaving some nations behind (Hasan et al. 2024; Demir et al. 2022).

These contradictory findings highlight several gaps in the literature. First, earlier papers used a single variable such as mobile cellular subscriptions to assess FinTech and FI indicators, neglecting the chance to capture the full advancement in financial technologies (Demir et al. 2022; Hou et al. 2024). Second, research into FinTech and sustainability in the European region is limited, focusing on only high-income or even a single country (Labidi 2025; Gao et al. 2024). Third, most of the research limits their focus to one or two environmental outcomes, resulting in a neglect of larger ecological implications (Liu 2025).

To address these gaps, this study contributes to multiple streams of literature. First, it captures a larger range of interactions by using five explanatory variables, FinTech, FI, green innovations (GI), NRR, and renewable energy (RE); and their impact on three environmental indicators: carbon dioxide emissions (CO_2), greenhouse gas emissions (GHG), and ecological footprints (EF). This provides holistic pictures of sustainability drivers (Demir et al. 2022; Kanga et al. 2022). Second, in contrast to previous research that depends on singular indicators for FinTech and FI, we construct composite indices through principal component analysis (PCA) to capture access, utilization, and quality of digital financial services. Third, this paper utilizes panel data from 31 European countries, covering wider geographical areas rather than focusing on only high-income or even a single country (Labidi 2025; Gao et al. 2024). The study covers the period between 2004 and 2021, to capture substantial advancements in digital finance and environmental policy, such as the approval of the Sustainable Development Goals[5]. Finally, we employ advanced panel econometric estimators to guarantee robust outcomes.

This paper is structured as follows. Section 2 discusses literature review. Section 3 presents the data and variable construction. Section 4 outlines the econometric methodology. Section 5 analyses the results. Section 6 discusses the results and offers policy recommendations. Section 7 concludes the study.

2 | Literature Review

2.1 | FinTech and FI

Initial research of FinTech highlighted its function in transforming financial services via technology (Arner et al. 2015), whereas FI was identified as a global development goal by the World Bank's Global Findex database (Demirguc-Kunt and Klapper 2012). Building on these foundations, recent studies established a connection between digital finance and sustainability outcomes. For example, FinTech increases financial services accessibility and lowers the barriers for underserved populations to engage in green investment and sustainable consumption (Goldstein et al. 2019). Digital financial tools, including mobile banking, blockchain, and peer-to-peer lending, drive the adoption of renewable energy, and improve the distribution of resources related to climate change (Rao et al. 2023).

Nevertheless, opposing research highlights the possible drawbacks of FinTech adoption. Wang et al. (2024) examined the impact of FinTech on corporate carbon emissions, finding that FinTech development causes a decrease in corporate CO_2 emissions. Meanwhile, Yao and Yang (2025) introduced the Climate Risk Index to investigate the role of FinTech on climate risks within financial markets. Their findings indicate that FinTech significantly increases climate risk within these markets. This contrast illustrates the persistent debate on whether FinTech acts as a "rebound amplifier" that raises energy consumption or as a "dematerializer" that boosts efficiency.

Overall, the literature indicates that FI and FinTech can enhance access to green finance and reduce emissions; nevertheless, rebound effects, such as increased energy demand, remain an issue. This motivates our first hypothesis regarding the possibly conflicting roles of FinTech and FI in influencing environmental outcomes.

2.2 | Green Innovation

The transition towards sustainability has gained attention globally as the efforts for sustainable development increase. Porter and Linde (1995) argued that well-structured environmental legislation can foster innovation, enhancing both competitiveness and sustainability. This "Porter Hypothesis" serves as the theoretical foundation for a significant portion of contemporary literature connecting innovation to environmental results. Recent studies have been built on this basis, offering empirical evidence regarding the environmental impact of green innovation. Umar and Safi (2023) revealed that green innovation decreases emissions in OECD countries, whereas Zhang et al. (2022) emphasize its significance in alleviating climate concerns. Simultaneously, certain academics observe that the environmental advantages of innovation can become apparent mostly in the long term, whereas short-term effects are less significant (Obobisa and Ahakwa 2024).

In general, the literature indicates that green innovation has a largely positive, but occasionally delayed, influence on environmental results. This supports our second hypothesis that green innovation is likely to enhance sustainability although its impacts may fluctuate over time and across different scenarios.

2.3 | Resource Rents and Renewables

The "resource curse" theory (Sachs and Warner 1995) offers an initial explanation for the ability of resource dependency to result in less favourable economic and environmental results. Likewise, Sadorsky (2009) illustrated the significance of renewable energy use in mitigating emissions, establishing a foundation for subsequent empirical investigations into the role of renewables in sustainability transitions. Building on these foundations, recent studies have examined the environmental influences of NRR and renewable energy. Many countries mainly rely on the extraction of fossil fuels as the primary source of revenue, thus causing a rise in ecological footprints (Lin 2024). Lu et al. (2023) revealed that natural resources adversely impact the environment in BRICKS countries, while Lin (2024) found that natural resources have a positive relation in the long run with ecological footprints in ASEAN countries. Simultaneously, the consumption of renewable energy continually acts as a mitigating factor, diminishing emissions and promoting sustainable growth (Obobisa and Ahakwa 2024).

In summary, resource rents are typically linked to environmental degradation, aligning with the "resource curse," whereas renewable energy causes reduction of emissions and ecological strain. This guides our third hypothesis regarding the contrasting roles of resource rents and RE in sustainability outcomes.

3 | Data and Variables

To obtain a measure of how financial innovation and resource use affect environmental outcomes in Europe, we gathered a panel dataset sample of 31 European countries. We exclude 12 countries[6] from the sample due to data unavailability across the full range of years and variables. The full country list is available in Appendix. Our dataset covers the period 2004–2021, after this period, data points are not available. We chose this timeframe to capture noteworthy global events, like the financial crisis of 2008. By examining this period, this study provides an insight into changes in the European climate that evolved over almost two decades. This timeframe is similar with previous studies such as Shah et al. (2025) and Chen et al. (2024).

Data comes from multiple sources. For example, CO_2 emissions, GHG emissions, renewable energy use, natural resource rents, gross domestic product per capita (GDP), and urbanization rates are from the World Development Indicators (WDI). FinTech indicators are from WDI and International Monetary Fund (IMF) datasets that are used to develop a composite fintech index. Ecological footprint data comes from the Global Footprint Network. Then, the green innovation metrics are from OECD's environment-related technologies patents. Finally, the FI index is measured using account ownership, ATM density, and digital payment access, which comes from the IMF and the Financial Access Survey (FAS) dataset.

Table 1 provides detailed descriptions of the variables, their measurement units, sources, and transformation procedures used in the empirical analysis.

3.1 | Dependent Variables

This study uses CO_2 emissions, greenhouse gas emissions, and ecological footprints as dependent variables. It assesses the environmental impact of FinTech and FI in European countries. CO_2 and GHG emissions (metric tons per capita) reflect the effect of fossil fuels on the climate and economic activity. Ecological footprints (global hectares per capita), however, show how the environment is under increased stress due to energy use and the usage of natural resources. Most prior studies (Obobisa and Ahakwa 2024; Wang et al. 2023) examine a single environmental outcome, usually CO_2 emissions, which restricts their capacity to assess wider ecological effects. To better understand how important environmental elements affect sustainability results, this study analyzes CO_2 emissions, GHG emissions, and EF all at once.

TABLE 1 | Variables, abbreviations, data sources, and measurements.

Title	Abbreviation	Source	Measurement
Carbon dioxide emissions	CO_2	WDI	Metric tons per capita
Greenhouse gas emissions	GHG	WDI	Metric tons of CO_2 equivalent per capita
Ecological footprint	EF	Global Footprint Network	Global hectares (gha) per capita
FinTech	FinTech	WDI, IMF	PCA index based on mobile subscriptions, internet use, financial development
Financial inclusion	FI	IMF	PCA index based on ATMs, bank branches, deposits, and loans (% of GDP)
Green innovation	GI	OECD	Number of environmental-related patent applications
Natural resource rents	NRR	WDI	% of GDP
Renewable energy	RE	WDI	% of total final energy consumption
GDP	GDP	WDI	GDP per capita (constant 2015 USD)
Urbanization	Urban	WDI	% of total population living in urban areas

3.2 | Independent Variables

3.2.1 | Fintech and FI Indices

This study utilizes PCA to create composite indices for both FinTech and FI variables, providing a more resilient evaluation of these diverse concepts. Consistent with Ahmad et al. (2024) and Hussain et al. (2023), this study develops the FinTech index based on the financial development index, the number of internet users, and the number of mobile subscribers. The FinTech index reflects the extent of digital financial penetration and technological progress. Similarly, this study develops FI index using the number of ATMs per 100,000 adults, the number of commercial bank branches per 100,000 adults, outstanding deposits with commercial banks (% of GDP), and outstanding loans from commercial banks (% of GDP). The developed FI index is in line with Hussain et al. (2023) and Huo et al. (2024). Higher index scores reflect deeper financial systems. Fintech and FI indices together measure the availability and utilization of financial services. Tables 2 and 3 provide details of PCA analysis.

3.2.2 | Other Independent Variables

Additionally, this study further incorporates three independent variables illustrated in Table 1. These are natural resource rents (NRR), GI, and renewable energy (RE). GI is measured by the number of patents for environment-related technologies. It displays technological developments meant to enhance

sustainability (Obobisa and Ahakwa 2024). NRR is a percentage of GDP and captures economic reliance on resource extraction, which can influence environmental degradation (Liu 2025). Lastly, RE is a percentage of total final energy consumption (Miao et al. 2024) and represents the shift toward cleaner energy sources by reducing carbon emissions.

3.3 | Control Variables

This study includes GDP per capita and urbanization (% of total population) as control variables, subsequent to prior studies, including Zhang et al. (2022) and Obobisa and Ahakwa (2024). GDP per capita captures economic development's impact on sustainability, while urbanization influences environmental pressures and energy usage.

3.4 | Sample Clusters

Along with the main sample of 31 European countries from 2004 to 2021, this dataset is further divided into three cluster samples for more in-depth analysis. The first cluster covers the top 10 European economies[7] (IMF World Economic Outlook 2024) ranked by GDP per capita. The second sample cluster comes from the COVID-19 pandemic period of 2020 and 2021. And the third sample cluster covers the financial crisis period of 2007–2008. The European countries in the first cluster are chosen for their high-income levels, developed financial systems, and

TABLE 2 | Principal component analysis results for FinTech index.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.729	0.877	0.576	0.576
Comp2	0.851	0.432	0.284	0.860
Comp3	0.418		0.139	1.000

Variable(s)	Comp1	Comp2	Comp3
Mobile_Subscriptions	0.526	0.709	0.468
Internet_Users	0.665	−0.001	−0.746
FD_Idx	0.528	−0.705	0.473

Note: Abbreviations: Mobile_Subscriptions = number of mobile subscribers; Internet_Users = number of internet users; and FD_Idx = financial development index.
Source: Author's calculations.

TABLE 3 | Principal component analysis results for financial inclusion index.

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.953	0.700	0.488	0.488
Comp2	1.253	0.502	0.313	0.801
Comp3	0.751	0.705	0.188	0.989
Comp4	0.042		0.010	1.0000

Variable(s)	Comp1	Comp2	Comp3	Comp3
ATM	0.095	−0.690	0.716	0.043
BankBranches	0.047	0.714	0.687	0.120
Deposits	0.705	0.030	−0.106	0.701
Loans	0.702	0.110	0.055	−0.702

Note: ATM = number of ATMs per 100,000 adults; BankBranches = number of commercial bank branches per 100,000 adults; Deposits = outstanding deposits with commercial banks; Loans = outstanding loans from commercial banks.
Source: Author's calculations.

leadership in digital finance and climate policy. It covers the full sample period from 2004 to 2021. The second and third clusters cover all 31 European countries as in the main sample; however, it differs in the sample period of 2004–2021. The second and third clusters examine how short-term shocks affect the environmental impact of the selected explanatory variables.

4 | Methodology

4.1 | Model Specification

The empirical analysis evaluates the effect of five primary independent variables on three environmental outcome indicators: CO_2 emissions, GHG emissions, and EF in a panel sample of 31 European countries. This study comprises two control variables (GDP per capita and urbanization) as well to consider the demographic and economic effects. All variables are log-transformed to minimize heteroscedasticity and enable interpretation based on elasticity, except for the FinTech and FI indices. The logarithmic form of the models in Equations (1–3).

$$
\begin{aligned}
\ln CO_{2it} = {} & \alpha_1 \ln CO2_{i,\ t-1} + \beta_1 FinTech_{it} + \beta_2 FI_{it} \\
& + \beta_3 \ln GI_{it} + \beta_4 \ln NRR_{it} + \beta_5 \ln RE_{it} \\
& + \gamma_1 \ln GDP_{it} + \gamma_2 \ln Urban_{it} + \mu_i + \lambda_t + \varepsilon_{it}^{CO2},
\end{aligned} \quad (1)
$$

$$
\begin{aligned}
\ln GHG_{it} = {} & \alpha_2 \ln GHG_{i,\ t-1} + \beta_1 FinTech_{it} + \beta_2 FI_{it} \\
& + \beta_3 \ln GI_{it} + \beta_4 \ln NRR_{it} + \beta_5 \ln RE_{it} \\
& + \gamma_1 \ln GDP_{it} + \gamma_2 \ln Urban_{it} + \mu_i + \lambda_t \\
& + \varepsilon_{it}^{GHG},
\end{aligned} \quad (2)
$$

$$
\begin{aligned}
\ln EF_{it} = {} & \beta_1 FinTech_{it} + \beta_2 FI_{it} + \beta_3 \ln GI_{it} + \beta_4 \ln NRR_{it} \\
& + \beta_5 \ln RE_{it} + \gamma_1 \ln GDP_{it} + \gamma_2 \ln Urban_{it} + \mu_i \\
& + \lambda_t + \varepsilon_{it}^{EF},
\end{aligned} \quad (3)
$$

where $\ln CO_{2it}$, $\ln GHG_{it}$ emissions, and $\ln EF_{it}$ serve as the dependent variables, represent carbon dioxide emissions, greenhouse gas emissions, and the ecological footprint in country i at time t. The lagged variables ($\ln CO2_{i,t-1}$ or $\ln GHG_{i,t-1}$) capture dynamic persistence in emissions, whereas ecological footprint is described without a lag because information criteria favoured a static formulation.

The primary independent variables are the Financial Technology (FinTech) and FI indices. Green Innovations ($\ln GI$), NRR

($\ln NRR$), and Renewable Energy ($\ln RE$) are additional independent variables. Per capita economic growth ($\ln GDP$) and urbanization ($\ln Urban$) are included as control variables.

μ_i represents unobserved country-specific fixed effects, while λ_t denotes year fixed effects to absorb time shocks common to all countries. The error structure follows AR(1) process. Lag length was determined by computing and comparing Akaike (AIC) and Bayesian (BIC) information criteria across $P = 0,1,2$; then selection favoured one lag for the CO_2 and GHG equations, while no lag was retained for the EF model. Online Appendix 1 is available that contains Stata code excerpts for reproducibility.

Figure 1 provides the econometric approaches used in this study.

4.2 | Cross-Sectional Dependence (CD) and Slope Heterogeneity (SH)

The empirical estimation begins with a CD test by Pesaran (2004) to make sure the results are unbiased. As in Shah et al. (2025) and Hossain et al. (2024), the data is tested for CD first to determine if the slopes are uniform across panels before calculating coefficient elasticities.

The CSD test is as follows.

$$
CSD = \sqrt{\frac{2T}{N(N-1)}} \ \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \partial_{ij} \rightarrow N(0,1), \quad (4)
$$

where ∂_{ij}:

$$
\partial_{ij} = \frac{\sum_{t=1}^{T} \epsilon_{it} \epsilon_{jt}}{\sqrt{\sum_{t=1}^{T} \epsilon_{it}^2} \sqrt{\sum_{t=1}^{T} \epsilon_{jt}^2}}, \quad (5)
$$

where T is the time dimension, N represents the cross-sectional dimension, ∂_{ij} is the pairwise correlation of the residual between cross-sectional units i and j. $N(0,1)$ is for the standard normal distribution. In addition, the Pesaran et al. (2008) slope coefficient homogeneity (SH) test is applied to check if slope coefficients remain consistent across panels.

4.3 | Panel Unit Root

After establishing the presence of SH and CD, we measure variable stationarity by applying second-generation unit root
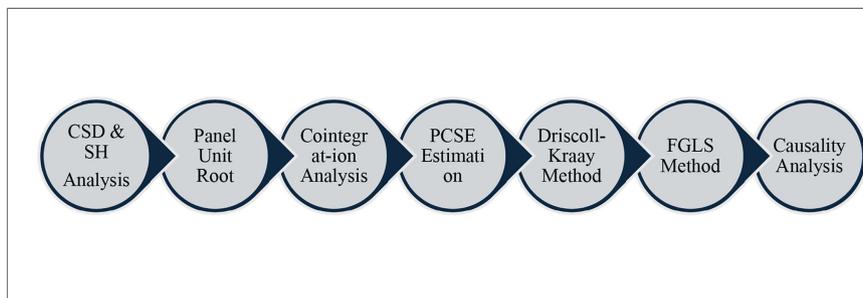

FIGURE 1 | Econometric approaches applied in this study. *Note:* This econometric approach ensures the reliability of the final outcomes since the analysis is conducted based on the results of each applied step.

tests. Specifically, the cross-sectional augmented Im-Pesaran (CIPS) and cross-sectional augmented Dickey-Fuller (CADF) tests. Zhang et al. (2022) concluded that first-generation stationarity tests may yield biased results in the presence of CD and SH. This issue makes second-generation tests a more reliable choice. The CIPS test is Equation (6).

$$\text{CIPS} = N^{-1}\text{CADF}, \qquad (6)$$

where N^{-1}CADF is the average of individual CADF statistics within cross-sectional units.

4.4 | Cointegration Analysis

We apply the Westerlund cointegration test to inspect the presence of long-term relationships among variables (Westerlund 2007). Compared to other traditional cointegration tests by Pedroni (1999) and Kao (1999), Westerlund's error correction mechanism (ECM) based test is preferred for its ability to account for both heterogeneity and CSD.

4.5 | Panel Corrected Standard Error Estimation (PCSE)

If complex error structures in panel data are ignored, the estimations of the coefficients will be inefficient, which will lead to underestimated standard errors, as well as ineffective coefficient estimations. For example, traditional panel regression techniques are ineffective when autocorrelation, heteroskedasticity, and cross-sectional dependence issues are present in panel data. Reed and Ye (2011) note that most of the conventional estimators do not account for the simultaneous handling of all the problems. Accordingly, the PCSE estimator, a two-stage modified OLS estimator, serves as our main model. This estimation method is used to yield superior outcomes, as suggested by Beck and Katz (1995). The PCSE estimation method considers the models' error terms to be autocorrelated within the panel and heteroskedastic across the panel. Furthermore, the autocorrelation parameter may be constant across panels or may differ for every panel, and it may be assumed that the error terms are autocorrelated inside the panel.

4.6 | Robustness Tests

We employ the Driscoll-Kraay (DK) and the feasible generalized least squares (FGLS) estimation methods to validate the robustness of the findings generated by the PCSE method.

4.6.1 | DK Standard Errors Method

We use the Driscoll and Kraay (1998) standard error method as a first-layer robust estimation technique to confirm the findings of our main estimator. Like PCSE, the DK method corrects for standard errors, accounts for heteroskedasticity, and considers serial correlation across panels, especially when CSD is present. Furthermore, this method is suitable for balanced as well as unbalanced panel data, making it a reliable complement to the models in our study. Lastly, this method's application as a robust estimator further strengthens its capability to generate

consistent results when there are missing values (Shah et al. 2025).

4.6.2 | FGLS Method

We use the FGLS technique as a second-layer robust estimation to further validate the findings of the main estimator (PCSE). The FGLS method controls for heteroscedasticity using robust standard errors. In addition, it models the autoregressive process, eradicating residual autocorrelation, especially when cross-sectional dependence is present in the dataset (López Prol and Zilberman 2023). By doing so, the FGLS method offers more efficient estimates and becomes a dependable addition to the models in our study.

4.7 | Dumitrescu-Hurlin (DH) Test of Causality

We test for the causation between the study's selected variables using the Dumitrescu and Hurlin (2012) causality test across panel units. It adds to the original Granger causality test established by Granger (1969), by allowing for heterogeneity in both the autoregressive structure and the causal coefficients among cross-sectional units as in Equation (7).

$$y_{it} = a_i + \sum_{j=1}^{J} \lambda_i^j \ y_{i(T-j)} + \sum_{j=1}^{J} \beta_i^j \ X_{i(T-J)} + e_{it}, \qquad (7)$$

where y_{it} represents dependent variables, X_{it} is for explanatory variables for unit i at time t. a_i is the individual fixed effect. λ_i^j, B_j^i are the lagged coefficients which may vary across units.

5 | Results Analysis

5.1 | PCA Analysis of Fintech and FI Indices

Table 2 displays the findings of the PCA for the FinTech index, which shows that the first principal component (PC1) holds an eigenvalue of 1.729. In contrast, the second principal component (PC2) has a marginally reduced eigenvalue of 0.851, and this figure consistently decreases with the third principal component (PC3), which holds an eigenvalue of 0.418. Consequently, PC1 was chosen as the main component for creating the FinTech index. Figure 2 displays the scree plot of the eigenvalues resulting from PCA. Further, the PCA findings of FI index are presented in Table 3. Like FinTech index, PC1 was the primary choice to construct FI index, since it has the highest eigenvalue among the four components. Figure 3 depicts the scree plot of the eigenvalues for the FI index following PCA analysis.

5.2 | Econometric Analysis

Table 4 shows the descriptive statistics of study variables. FinTech and FI indices are all standardized, thus showing a mean of zero and about 1.3 standard deviation. This indicates that digital financial adoption represents a volatile level of variation. The variables with the highest mean values are lnGDP, lnGI, and lnUrban with means of (9.991), (6.525), and (4.238) respectively. This shows high average levels of economic
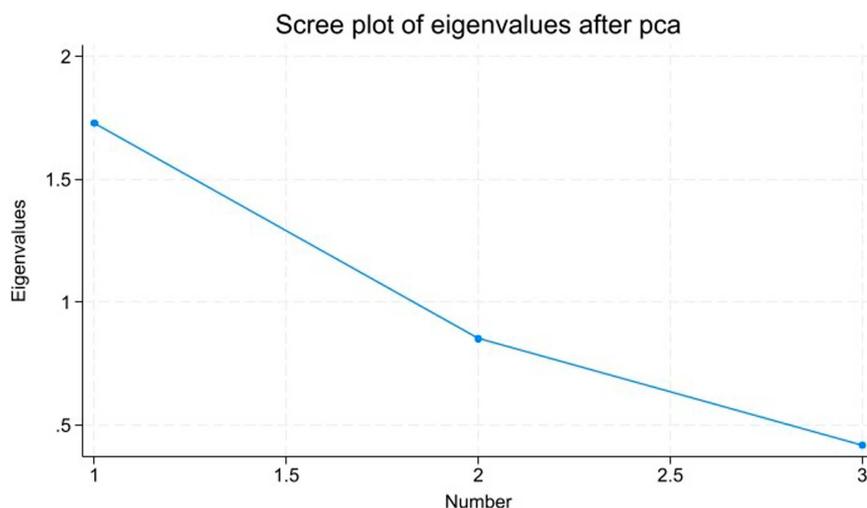
FIGURE 2 | Scree plot of the eigenvalues of FinTech PCA. *Source:* Author's calculations.
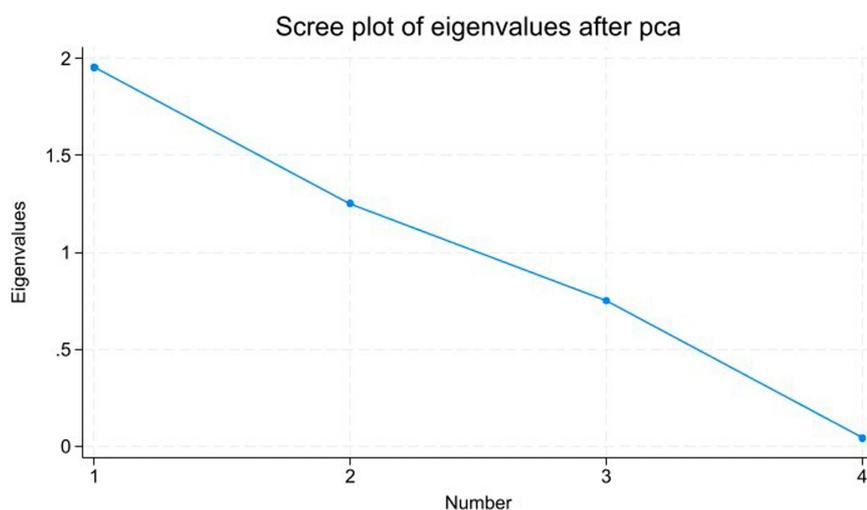

FIGURE 3 | Scree plot of the eigenvalues of FI PCA. *Source:* Author's calculations.

TABLE 4 | Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max	JB statistics
lnCO2	558	1.936	0.408	0.963	3.26	12.24***
lnGHG	558	2.198	0.361	1.288	3.335	8.515**
lnEF	558	1.615	0.364	0.421	2.74	59.36***
FinTech	558	0	1.315	−5.203	2.315	195.4***
FI	558	0	1.398	−1.254	7.961	8757***
lnGI	558	6.525	0.165	5.92	6.636	1874***
lnNRR	558	−1.087	1.559	−5.349	2.535	6.88**
lnRE	558	2.737	0.788	0.095	4.117	52.97***
lnGDP	558	9.991	0.955	7.485	11.63	38.06***
lnUrban	558	4.238	0.198	3.749	4.586	29.26***

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; FI = financial inclusion; FinTech = financial technology; $lnCO_2$ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization.
Source: Author's calculations.

activity. Additionally, Jarque and Bera (1987) (JB) test for normality reveals that most data lack symmetries and are non-normally distributed, which calls for the use of non-parametric techniques. In summary, the results indicate that there are no major outliers which support the dataset being reliable for regression analysis.

Table 5 displays the correlation matrix. It indicates the linear correlations among variables. The results imply that $lnCO_2$ is highly correlated with lnGHG emissions at $r = 0.978$. Similarly, high correlation exists between $lnCO_2$ and lnEF ($r = 0.740$), implying these environmental indicators tend to rise and fall together. Furthermore, FinTech shows a positive correlation with $lnCO_2$, lnGHG, and lnEF, while FI is negatively associated with the study's dependent variables, indicating an inverse relationship. Nonetheless, the results show no evidence to exclude any of these variables from the analysis.

Next, we test for the possible multicollinearity issue among explanatory variables, using the variance inflation factor (VIF) test to validate the regression results, as shown in Table 6. The VIF values are between 1.020 and 3.653, with a mean VIF of 1.985, which is far lower than the usual threshold of 10. This indicates that multicollinearity was not an issue, and the factors are acceptable to be included in the econometric estimations.

As a result, and to decide about the time-series characteristics of the data, this study applies the Cross-sectionally Augmented Dickey-Fuller (CADF) and Cross-sectionally Augmented IPS (CIPS) unit root tests. These tests are applicable for panels characterized by cross-sectional dependence and heterogeneity (Javed et al. 2024). The outcomes in Table 7 reveal that most variables are non-stationary at level and become stationary after first difference. This proves that variables are order one, I (1) integrated, which is an essential requirement for doing panel cointegration analysis. Moreover, strong evidence of cross-sectional dependence is clear from the CSD test statistics. This ensures that panel cointegration and second-generation tests may be employed to consider the dependence across units.

In addition, Pesaran et al. (2008) proposed to test for slope coefficients' uniformity across cross-sectional units using the slope coefficient homogeneity (SH) test. Table 8 presents the

findings, which reject the null hypothesis of slope homogeneity for all three models, $lnCO_2$, lnGHG, and lnEF, for both the standard and HAC robust specifications ($p < 0.01$). Also, we use the same test to verify parameter consistency across countries. These findings support the need to move forward with panel cointegration analysis, as does the existence of cross-sectional dependency and unit root features.

This study utilizes the Westerlund (2007) cointegration test to evaluate the long-run relationship between the study's variables. The outcome in Table 9 reveals that in the long run, there is no cointegration in $lnCO_2$ and lnGHG models. However, for the lnEF model, the results show that only the Gt statistic is significant at the 1% level. This might suggest the existence of weak cointegration.

Following the preliminary estimations, we test the influence of our explanatory variables on CO_2 emissions, GHG emissions, and EF. The PCSE regression analysis's findings are displayed in Table 10. The findings indicate that FinTech, FI, lnGI, lnNRR, and lnGDP are all statistically significant with environmental indicators. FinTech, FI, and lnRE are all negatively associated with $lnCO_2$, lnGHG, and lnEF. A 1% increase in FinTech led to

TABLE 6 | Variance inflation factor.

	VIF	**1/VIF**
FinTech	3.286	0.304
FI	1.034	0.967
lnGI	1.02	0.98
lnNRR	1.417	0.705
lnRE	1.306	0.766
lnGDP	3.653	0.274
lnUrban	2.176	0.46
Mean VIF	1.985	

Note: FI = financial inclusion; FinTech = financial technology; $lnCO_2$ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGI = natural log of green innovation; lnGHG = natural log of greenhouse gas emissions; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization.
Source: Author's calculations.

TABLE 5 | Pairwise correlations.

Variables	lnCO2	lnGHG	lnEF	FinTech	FI	lnGI	lnNRR	lnRE	lnGDP	lnUrban
lnCO2	1.000									
lnGHG	0.978	1.000								
lnEF	0.740	0.753	1.000							
FinTech	0.315	0.297	0.510	1.000						
FI	−0.119	−0.140	−0.049	0.106	1.000					
lnGI	0.059	0.055	0.032	0.029	0.039	1.000				
lnNRR	−0.063	−0.031	−0.213	−0.318	−0.079	0.051	1.000			
lnRE	−0.340	−0.316	−0.064	0.213	0.068	−0.050	0.179	1.000		
lnGDP	0.479	0.471	0.729	0.801	0.075	−0.027	−0.456	0.103	1.000	
lnUrban	0.429	0.406	0.621	0.627	−0.038	−0.018	−0.216	−0.124	0.654	1.000

Note: FI = financial inclusion; FinTech = financial technology; $lnCO_2$ = natural log of carbon dioxide; lnEF = natural log of ecological footprint, lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization.
Source: Author's calculations.

TABLE 7 | Cross-sectional dependence and unit-root test result.

Variables	CSD Test	CIPS unit root test		CADF unit root test	
		Level	1st difference	Level	1st difference
lnCO2	43.205	−2.224	−4.417***	−2.224	−4.417***
lnGHG	38.426	−2.221	−4.434***	−2.221	−4.434***
lnEF	38.701	−2.973	−4.633***	−2.973	−4.633***
FinTech	81.394	−2.955	−4.555***	−2.955	−4.555***
FI	66.770	−1.747	−3.502***	−1.747	−3.502***
lnGI	91.488	1.700	1.700	1.700	1.700
lnNRR	38.684	−2.601	−3.823***	−2.601	−3.823***
lnRE	76.941	−3.001	−4.422***	−3.001	−4.422***
lnGDP	57.288	−1.885	−3.308***	−1.885	−3.308***
lnUrban	52.474	−1.384	−1.835	−1.384	−1.835

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; FI = financial inclusion; FinTech = financial technology; lnCO2 = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product, lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization.
Source: Author's calculations.

TABLE 8 | Slope heterogeneity tests.

Test type	Model 1: lnCO2		Model 2: lnGHG		Model 3: lnEF	
	Δ	Adj. Δ	Δ	Adj. Δ	Δ	Adj. Δ
Standard test	8.176***	11.562***	8.582***	12.136***	8.711***	12.319***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HAC robust test	8.041***	11.371***	11.604***	16.411***	10.005***	14.150***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: * = 10% level of significance, ** = 5% level of significance, and *** = 1% level of significance. *p*-values in parentheses.
Source: Author's calculations.

TABLE 9 | Westerlund (2007) cointegration test.

Test	CO2	GHG	EF
Gt	−1.701 (0.418)	−1.591 (0.523)	−2.736*** (0.003)
Ga	−2.666 (0.763)	−2.626 (0.730)	−2.059 (0.973)
Pt	−9.160 (0.215)	−8.515 (0.293)	−10.173 (0.105)
Pa	−3.101 (0.360)	−2.981 (0.408)	−2.484 (0.670)

Note: * = 10% level of significance, ** = 5% level of significance; *** = 1% level of significance. *p*-values in parentheses.
Source: Author's calculations.

0.018%, 0.026%, and 0.073% decrease in lnCO2, lnGHG, and lnEF, respectively. A similar effect applies for FI and lnRE. This suggests that financial innovations help reduce environmental pressure, along with renewable energy's effect on minimizing environmental damage. These results are supported by earlier studies of Alsedrah (2024), and Zhang et al. (2024).

Moreover, lnGI and lnNRR are found to be positively associated with all environmental indicators. lnCO2, lnGHG, and lnEF increase by 0.113%, 0.096%, and 0.0126%, respectively, for every 1% increase in lnGI. This indicates that more green innovations and resource exploitation lead to increased environmental degradation. The findings of Chien et al. (2024) for Asian economies and Obobisa and Ahakwa (2024) for 25 European Countries align with our findings.

Lastly, lnUrban shows mixed results. It reveals insignificance with lnCO2, weak significance with lnGHG, and positive significance with lnEF. This discrepancy demonstrates the various ways in which urbanization can operate; in certain situations, clean technologies and effective infrastructure in cities may balance off direct CO2 emissions, while population density and patterns of transportation raise GHG emissions. At the same time, the ecological footprint grows due to the increased demand for resources, energy, and land in metropolitan areas.

The findings of Ahmad et al. (2024) are consistent with our results. They found that urbanization is beneficial to the environment in developed economies, while it tends to increase emissions and EF in developing economies.

5.3 | Robustness Analysis

This study uses Driscoll and Kraay standard error methods and FGLS estimation methods to validate the results of PCSE technique. The findings in Table 11 depict the results of the PCSE estimator, across all three environmental indicators, in sign, magnitude, and statistical significance. Both FinTech and FI help reduce environmental deterioration, and lnRE reduces environmental pressure. These findings are similar to other studies such as Hussain et al. (2023). Online Appendix 2 contains additional test results from the robustness analysis, for example, F-statistics, adjusted R^2, Wooldridge serial-correlation tests, and the Newey-West window length employed for DK standard errors. These additional tests show coefficient signs and magnitudes are consistent among the three estimators (PCSE, DK, and FGLS), demonstrating the stability of our findings. While PCSE gives significantly greater standard errors, DK produces substantially smaller errors, while FGLS yields the smallest errors. Although this pattern shows the variations in efficiency across the estimators, the stability of our results is

confirmed by the convergence of coefficient magnitudes and significance among all three models.

The consistent results of the robustness tests with the findings of the main model highlight the important role of financial technologies and resource drivers in influencing environmental performance. Our findings are not only consistent with other researchers in other domains, but also the significance results provide credible evidence of how climate targets and digital finance adoption are at the heart of policy frameworks across the European region.

The previous results from the PCSE, DK, and FGLS methods presented the effect of every explanatory variable on CO_2 emissions, GHG emissions, and EF. Nevertheless, there is still a necessity to examine the causal link between the variables. Thus, in this study, we apply Dumitrescu and Hurlin (2012) causality analysis to additionally validate the previous results. The findings in Table 12 indicate that all explanatory variables, except for lnGI, cause environmental indicators. This supports the main findings that these variables drive environmental outcomes.

5.4 | Cluster-Based Comparative Analysis

To complement the outcomes from the full European panel, this study also looks at three cluster samples. The first-cluster sample considers the top ten economies in Europe. The countries are classified based on their GDP per capita, consistent with the IMF World Economic Outlook Database (2024). It covers the period (2004–2021) and follows the same methodological process as in the full sample. However, the second cluster sample covers the period (2020–2021) to test the effect of the Covid-19 pandemic. Studies such as Guo et al. (2025) and Huang et al. (2023) also used this period to define the Covid-19 pandemic era. This cluster includes all the 31 European countries as in the main sample. Moreover, the third cluster sample studies the effect of independent variables on environmental outcomes during the 2007–2008 financial crisis. Hossain et al. (2024) and Madeira (2024) used this timeframe to represent the financial crisis period. This sample also includes all the 31

TABLE 10 | PCSE estimation method results.

Variables	lnCO2	lnGHG	EF
FinTech	−0.018***	−0.026***	−0.073***
FI	−0.033***	−0.034***	−0.016***
lnGI	0.113***	0.096***	0.126***
lnNRR	0.083***	0.082***	0.038***
lnRE	−0.232***	−0.198***	−0.042***
lnGDP	0.311***	0.296***	0.334***
lnUrban	−0.000	−0.051**	0.433***
Cons	−1.188***	−0.539**	−4.217***

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; Cons = constant; FI = financial inclusion; FinTech = financial technology; $lnCO_2$ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization; PCSE = panel corrected standard error estimation method.
Source: Author's calculations.

TABLE 11 | Results of Driscoll-Kraay and FGLS estimation methods.

Method variables	Driscoll-Kraay			FGLS		
	CO2	GHG	EF	CO2	GHG	EF
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
FinTech	−0.019**	−0.026***	−0.073***	−0.018***	−0.026***	−0.072***
FI	−0.033***	−0.035***	−0.016***	−0.033***	−0.034***	−0.017***
lnGI	0.114***	0.096***	0.126***	0.114***	0.095***	0.091***
lnNRR	0.083***	0.082***	0.038***	0.082***	0.081***	0.038***
lnRE	−0.232***	−0.199***	−0.042***	−0.232***	−0.197***	−0.043***
lnGDP	0.311***	0.296***	0.334***	0.310***	0.295***	0.333***
lnUrban	−0.000	−0.051*	0.433***	−0.005	−0.052***	0.433***
Cons	−1.188***	−0.540*	−4.217***	−1.162***	−0.525***	−3.990***

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; Cons = constant; FGLS = feasible generalized least square estimation method; FI = financial inclusion; FinTech = financial technology; $lnCO_2$ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization.
Source: Author's calculations.

European countries. These subsamples provide further comparison of different economic structures and time-specific events. Therefore, providing more insights into the stability and variability of environmental drivers.

5.4.1 | Cluster 1—Top 10 Economies by GDP Per Capita

In this high-income group, the main findings of FI, lnNRR, and lnRE in Table 13 remain consistent as in the main sample. However, FinTech exhibits no effect on lnCO₂ emissions, a small effect on lnGHG emissions, and strong negative significance with lnEF. This suggests that while FinTech plays a minor effect on emissions, it significantly supports ecological sustainability in wealthy economies. Additionally, lnGI shifts to become significantly negatively associated with environmental indicators. This highlights that the actual outcomes of GI are better translated in the top economies. In addition, lnUrban turns to being harmful in this sample, possibly due to the advanced consumption patterns found in metropolitan areas. Meanwhile, the environmental impact of lnGDP diminishes for both CO₂ and GHG but still exhibits the same effect on EF. This indicates that consumption patterns in wealthier countries cause economic growth to have a higher impact on EF than direct emissions.

TABLE 12 | Dumitrescu-Hurlin causality test results.

Direction	W-bar	Z-bar Stat	p value
FinTech → lnCO₂	2.458	5.740	0.000
FI → lnCO₂	2.001	3.939	0.000
lnGI → lnCO₂	1.599	2.360	0.018
lnNRR → lnCO₂	1.829	3.264	0.001
lnRE → lnCO₂	3.769	10.904	0.000
lnGDP → lnCO₂	4.532	13.907	0.000
lnUrban → lnCO₂	5.053	15.956	0.000
FinTech → lnGHG	2.350	4.921	0.000
FI → lnGHG	1.796	3.133	0.002
lnGI → lnGHG	1.491	1.935	0.053
lnNRR → lnGHG	1.967	3.809	0.000
lnRE → lnGHG	3.553	10.050	0.000
lnGDP → lnGHG	4.250	12.796	0.000
lnUrban → lnGHG	5.189	16.491	0.000
FinTech → lnEF	2.626	6.403	0.000
FI → lnEF	2.915	7.539	0.000
lnGI → lnEF	1.388	1.527	0.127
lnNRR → lnEF	1.881	3.468	0.000
lnRE → lnEF	5.722	18.591	0.000
lnGDP → lnEF	4.799	14.959	0.000
lnUrban → lnEF	6.184	20.411	0.000

Note: Abbreviations: FI = financial inclusion; FinTech = financial technology; lnCO₂ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization.
Source: Author's calculations.

5.4.2 | Cluster 2—COVID-19 Pandemic Period (2020–2021)

In the 2-year cluster, we apply the same PCSE estimator as in the main sample. The key findings of the independent variables in Table 14 are identical to the results derived from the original sample. The only difference is with lnUrban, where it becomes significantly negatively correlated with lnCO₂, lnGHG, and lnEF. It could be a result of travel constraints that were imposed at that time. These findings confirm the significance of FinTech, FI, and RE as drivers of an environmentally friendly economy, even under a global crisis. It also validates the need to reassess green innovation policies and resource dependency.

5.4.3 | Cluster 3—2008 Financial Crisis (2007–2008)

Table 15 presents the main findings for this timeframe. The outcomes reveal that FinTech, lnNRR, lnRE, and lnGDP have

TABLE 13 | PCSE estimation results for top 10 economies.

Variables	lnCO2 Coefficient	lnGHG Coefficient	lnEF Coefficient
FinTech	−0.021	−0.019*	−0.037***
FI	−0.064***	−0.066***	−0.084***
lnGI	−0.020***	−0.024***	−0.071***
lnNRR	0.014***	0.012***	0.015***
lnRE	−0.284***	−0.246***	−0.110***
lnGDP	0.040	−0.020	0.190***
lnUrban	0.079**	0.219***	0.559***
Cons	2.038***	2.211***	−2.009***

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; Cons = constant; FI = financial inclusion; FinTech = financial technology; lnCO₂ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization, PCSE = panel corrected standard error estimation method.
Source: Author's calculations.

TABLE 14 | PCSE estimation results for covid-19 period.

Variables	lnCO2 Coefficient	lnGHG Coefficient	lnEF Coefficient
FinTech	−0.218***	−0.239***	−0.272***
FI	−0.074***	−0.085***	−0.082***
lnGI	0.094***	0.125***	0.120***
lnNRR	0.051***	0.064***	0.081***
lnRE	−0.223***	−0.223***	−0.252***
lnGDP	0.140***	0.210***	0.183***
lnUrban	−1.636***	−1.691***	−1.389***
Cons	−3.604***	−3.564***	−3.666***

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; Cons = constant; FinTech = financial technology; FI = financial inclusion; lnCO₂ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization; PCSE = panel corrected standard error estimation method.
Source: Author's calculations.

TABLE 15 | PCSE estimation results for 2008 financial crisis.

Variables	lnCO2 Coefficient	lnGHG Coefficient	lnEF Coefficient
FinTech	−0.153***	−0.173***	−0.145***
FI	−0.017***	−0.021***	0.003
lnGI	−0.129	−0.068	0.965***
lnNRR	0.099***	0.098***	0.031***
lnRE	−0.206***	−0.187***	−0.035**
lnGDP	0.494***	0.504***	0.433***
lnUrban	0.323***	0.255***	0.593***
Cons	−2.800	−2.825***	−11.337***

Note: * = 10% level of significance; ** = 5% level of significance; *** = 1% level of significance; Cons = constant; FI = financial inclusion; FinTech = financial technology; $lnCO_2$ = natural log of carbon dioxide; lnEF = natural log of ecological footprint; lnGDP = natural log of gross domestic product; lnGHG = natural log of greenhouse gas emissions; lnGI = natural log of green innovation; lnNRR = natural log of natural resource rents; lnRE = natural log of renewable energy; lnUrban = natural log of urbanization; PCSE = panel corrected standard error estimation method.

Source: Author's calculations.

the same effects as in the main sample. Meanwhile, FI lost its force to reduce its ecological footprint. In addition, lnUrban shifts its influence to do more harm to the environment, possibly because of the increased demand for infrastructure. Also, lnGI turns out to be insignificant for $lnCO_2$ and lnGHG but positive and significant on lnEF with a coefficient of 0.965. This coefficient value of lnGI can be explained by "innovation gestation lag theory", which argues that green technologies′ advantages may become apparent on the medium to long term. Green innovation may increase the pressure on EF in the short term because it requires a substantial number of resources for research, development, and early deployment. Various studies have identified the same effect. For example, Mongo et al. (2021), found that the benefits of GI in reducing emissions mostly emerge over time, while Chien et al. (2024) noted that the immediate effects were unclear in BRICS economies. Likewise, Obobisa and Ahakwa (2024) pointed out that the environmental benefits of green technology adoption in Europe are delayed due to the high costs and skill sets involved.

5.4.4 | Evaluation of Cluster-Specific Outcomes

For all clusters, FinTech, FI, NRR, RE, and GDP roles are shown to be statistically significant in almost all cases. In contrast, GI and Urban appear to have different effects on the environment during different global crises. In conclusion, this analysis provides evidence for the need for policies that can be adapted under multiple global disruptions; not all tools perform the same under every situation.

6 | Discussion and Policy Implications

Our study finds that while NRR contributes to ecological pressures and urbanization has inconsistent effects across various metrics, FinTech, FI, and renewable energy greatly enhance environmental outcomes in Europe. Consistent across PCSE, DK, and FGLS estimations, these results offer strong evidence for the contribution of innovation, digital finance, and renewable energy in advancing sustainability goals.

6.1 | Digital Finance

Our findings reveal that both FinTech and FI considerably lowers environmental outcomes in Europe. These findings remain consistent with Driscoll-Kraay, FGLS, and PCSE estimators, increasing confidence in the digital financial channel. Similar results are provided by Xiao et al. (2024) and Ahmad et al. (2024), who demonstrate that FinTech and FI promotes green transitions and reduces ecological footprints in European nations.

Nonetheless, the impact of digital finance differs between developed and developing economies. It also varies during crisis, making these differences crucial for policymakers. For example, we found that for wealthy nations, FinTech impact in reducing emissions shows lower significance. Consistent with Demir et al. (2022), who highlighted that in high-income countries, the coefficient of FinTech shrinks and loses significance. One important implication is that digital banking needs to change from merely increasing accessibility to actively promoting environmentally friendly practices. This involves including carbon-tracking tools and Environmental, Social, and Governance (ESG) data into digital platforms in developed economies so that finance may direct consumers toward low-emission options. Expanding inclusion is still essential in less developed countries, but it should be linked to green use-cases like micro solar systems, energy-efficient appliances, or funding green projects. To prevent FinTech's environmental benefits from being diminished as it grows, incentives and risk-sharing programs could be connected to quantifiable environmental results on digital platforms at the European level.

6.2 | Renewable Energy

Our findings reveal that renewable energy continuously lowers CO_2 emissions, GHG emissions, and ecological footprints. Zhang et al. (2022) also revealed that renewable energy reduces CO_2 emissions in the G-20 economies. These consistent findings support the notion that renewable energy is key element of the green transition and reinforce the European Union's plan to become carbon neutral by 2050.

Accordingly, increasing the use of renewable energy is among the most effective strategies to produce measurable environmental benefits. To increase energy security and system efficiency, European governments should emphasize long-term investments in renewable infrastructure, expand cross-border renewable energy projects, and raise private capital via tools like green bonds. Europe may keep advancing toward sustainability by underpinning these policies to legally binding emission targets for renewable energy.

6.3 | Resource Dependence

The results of NRR and GI are divergent. Across the three models, NRR and GI are both positive and significant in the main sample. This implies that while innovation does not yet reduce environmental pressure, resource dependency does. One possible explanation is that new technologies frequently increase expenses, and energy demands before their benefits become apparent.

The findings varied for the top ten European economies. In this cluster sample, GI is negative and significant, highlighting how innovation lowers emissions in developed markets. NRR continues to be negative, as in the main sample. However, during the Covid-19 cluster sample, the outcomes are similar to the main sample with both NRR and GI continuing to be positive and significant. In the 2008 financial crisis cluster, however, GI becomes negative but not significant under CO2 and GHG models and becomes positive and significant under EF models. This indicates that innovation does not reduce emissions amid severe financial shocks and, in some cases, increases ecological pressure.

These findings demonstrate that the effect of innovation depends on circumstances. Green innovation lowers emissions and performs better in developed economies. Its impact is less pronounced or delayed in other nations and at times of crisis. This result shaped the policy implication in that Europe must implement fiscal and tax reform that limits its reliance on extraction to lessen its dependency on resource rents. Meanwhile, support for green innovation must be better targeted. Advanced economies should exchange innovative technologies and increase their Research and Development (R&D) budgets. Other countries must focus on developing long-term initiatives in order for innovation to eventually provide significant environmental advantages. Lastly, governments should protect innovation funding during times of crisis to avoid cutting green projects at the most critical times.

7 | Conclusion

This study evaluates how FinTech, FI, natural resource rents, green innovation, and renewable energy, affect CO_2 emissions, GHG emissions, and ecological footprint. It covers the European region for the period 2004–2021. The paper emphasizes how financial innovation and digital finance affect environmental sustainability by using panel econometric estimators, such as PCSE, DK, and FGLS methods, while also creating composite indices for FinTech and FI using PCA.

The empirical findings show that FinTech, FI, and RE significantly benefit CO_2 emissions, GHG emissions, and EF. While GI, NRR, and GDP put more pressure on all three environmental indicators. Additionally, EF was most significantly impacted by the level of urbanization, indicating that EF deteriorates as more people live in urban areas. These conclusions are all validated by the DH causality test results. This emphasizes the need to increase the alignment between FinTech, FI, GI, NRR, RE, GDP, and urbanization on environmental frameworks.

This study adds to the body of literature in several ways. First, it contributes to the empirical evidence on the impacts of financial technologies and innovations on environmental outcomes in the European region. Second, the study uses PCSE estimation method together with DK and FGLS as robustness checks, providing reliable results for all three environmental indicators. Third, the study assesses the influence of its indicators during key global events (Covid-19 and 2008 financial crisis), thus contributing timely policy relevance for the European region. Finally, these contributions provide more understanding of how financial technologies and innovations can either advance or hinder environmental sustainability.

The findings and contributions provide various policy implications. First, governments ought to promote the growth of environmentally friendly FinTech solutions through supporting regulatory sandboxes and green digital finance. Second, policymakers should enhance FI strategies that are linked to environmental goals, such as green microfinance programs. This will allow the underserved populations to engage in climate-friendly actions. Third, it is significant to improve the effect of green innovation by reinforcing the connection between R&D expenditures and environmental goals. Fourth, both NRR and GDP need to be managed wisely, especially in reducing the overall ecological stress by diversifying green growth strategies. Finally, European economies need to implement policies that bring together clean energy with sustainable urban development within a unified policy framework to adopt a sustainable future. A legal environment that connects digital finance with climate goals can help the European Green Deal and the UN Sustainable Development Goals move forward faster.

Additional insights are gained from the cluster-based analysis of high-income economies, the Covid-19 pandemic period, and the 2008 financial crisis. The results offer a further comparison of different economic structures and time-specific events. Therefore, providing more insights into the stability and variability of environmental drivers.

In the future, this research could be extended to include new political events that occurred after the year 2021 and by including other geographical regions, such as the Middle East, China and the United States.

Data Availability Statement

Data will be available on request from the authors.

Endnotes

[1] Global Footprint Network 2022 Annual Report.

[2] In 2019, the European Commission introduced the European Green Deal as strategic policy plan for preserving biodiversity, clean energy, and sustainable industry to achieve climate neutrality in the EU by 2050. *Source*: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52019DC0640

[3] In July 2021, the European Commission introduced the "Fit for 55" bundle, a collection of legislative measures aimed at reducing greenhouse gas emissions by a minimum of 55% by year 2030 in the EU. *Source*: https://www.consilium.europa.eu/en/policies/fit-for-55/

[4] In response to Ukraine's invasion by Russia in 2022, the European Commission has proposed REPowerEU, a strategy to eliminate dependency on Russian fossil resources by 2030. *Source*: https://commission.europa.eu/topics/energy/repowereu_en

[5] The Sustainable Development Goals includes 17 global goals adopted by all UN member states in 2015, designed to eradicate poverty, protecting the earth, and ensuring peace and prosperity by 2030. *Source*: https://sdgs.un.org/2030agenda

[6] Twelve European countries are excluded due to data unavailability: Albania, Andorra, Belarus, Iceland, Liechtenstein, Malta, Monaco, Montenegro, North Macedonia, San Marino, Serbia, and Russia.

[7]This sample focuses on the top 10 economies in Europe: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Luxembourg, Netherlands, and Sweden.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Online Appendix (1) - Stata Codes. Online Appendix (2) - DK & FGLS Robustness Checks Results.

Appendix

See Table A1

TABLE A1 | Full country list.

	Country
1	Austria
2	Belgium
3	Bosnia and Herzegovina
4	Bulgaria
5	Croatia
6	Czechia
7	Denmark
8	Estonia
9	Finland
10	France
11	Germany
12	Greece
13	Hungary
14	Ireland
15	Italy
16	Latvia
17	Lithuania
18	Luxembourg
19	Moldova
20	Netherlands
21	Norway
22	Poland
23	Portugal
24	Romania
25	Slovak Republic
26	Slovenia
27	Spain
28	Sweden
29	Switzerland
30	Ukraine
31	United Kingdom