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Evaluating the Impact of Renewable Energy Transition on Environmental Sustainability: Evidence Using Quantile Regression

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Abstract:

This study aims to analyze the impact of transitioning from traditional fossil fuel-based energy systems to renewable energy systems on promoting the green economy and sustainable development in industrial countries. Second-generation techniques for dynamic panel estimation, including Quantile Regression (MMQR) and Causality Tests (Dumitrescu & Hurlin, 2012), were used to analyze data from 29 industrial countries for the period 1990-2021. The results showed that increasing the use of renewable energy significantly reduces the environmental footprint, thus enhancing environmental sustainability. However, the effect was less pronounced at higher quantiles due to technological saturation, the intensity of economic activities, and infrastructural complexities. The study also found that economic growth increases the environmental footprint, while higher levels of education and trade openness contribute to its reduction. The study recommends adopting comprehensive policies that encourage the use of renewable energy, improve energy infrastructure, and enhance education to achieve a balance between economic growth and environmental protection, contributing to sustainable development and the green economy in industrial countries.

Keywords: Energy Transition; Renewable Energy; Green Economy; Environmental Footprint.

1. Introduction

In the contemporary global economy, the environmental crisis characterized by climate change, natural resource depletion, and unprecedented pollution levels has compelled the global community to seek transformative solutions that embrace renewable energy sources. This strategy is increasingly viewed as central to enhancing economic resilience while ensuring environmental sustainability. The transition from fossil fuel-based energy systems to ren

The deployment of renewable energy sources is expected to trigger a range of positive economic externalities. These include the creation of green jobs, the stimulation of innovation and technological advancement, and the potential to usher in a new era of economic prosperity grounded in environmental stewardship (Çakmak & Acar, 2022). The use of renewable energies is seen as a mechanism to decouple economic growth from carbon emissions, fostering a green economy characterized by low carbon output, natural resource conservation, and a harmonious balance between human activities and ecosystems (Dogan & Inglesi-Lotz, 2017).

In industrialized countries, the scenario is even more critical, as these nations have historically been significant contributors to environmental degradation due to their reliance on carbon-intensive energy sources. Therefore, the shift towards renewable energies in these countries is not merely a matter of policy transformation but a vital necessity to mitigate further environmental deterioration and prioritize sustainable practices (Balaguer & Cantavella, 2018).

2. Literature Review

Research on the relationship between renewable energy and environmental quality has yielded mixed results, with some studies confirming a positive impact while others suggesting an insignificant or limited effect. For instance,(Çakmak & Acar, 2022) found that renewable energy consumption had no significant impact on the ecological footprint in major oil-producing countries, despite economic growth significantly increasing it.(Saud et al., 2023) observed that economic complexity and natural resource abundance negatively impacted carbon dioxide emissions and the ecological footprint in the Middle East and North Africa countries, whereas education and financial development positively influenced environmental sustainability, thereby demonstrating the Environmental Kuznets Curve (EKC) phenomenon. Similarly, (Balaguer & Cantavella, 2018) highlighted the crucial role of education in offsetting the rise in per capita carbon dioxide emissions driven by economic growth in Australia. (S. P. Nathaniel et al., 2021) found that while economic growth and natural resource exploitation increased the ecological footprint in Brazil, Russia, India, China, and South Africa (BRICS countries), renewable energy consumption reduced it, indicating that further development of human capital is essential for effective environmental mitigation. Additionally, (Çakmak & Acar, 2022)emphasized the critical role of economic complexity and renewable energy in meeting the environmental targets set by the 21st Conference of the Parties (COP21). Studies by (Saud et al., 2023) and (S. P. Nathaniel et al., 2021)underscore the necessity of sustainable resource management and the adoption of innovative technologies to achieve environmental sustainability in BRICS and Group of Seven (G7) countries.

Moreover, (Dogan & Inglesi-Lotz, 2017) investigated the impact of biomass energy consumption on CO2 emissions within the EKC framework for 18 biomass-consuming countries from 1990 to 2014. They found that biomass energy consumption reduces CO2 emissions, suggesting that investment in biomass energy infrastructure could be an effective policy for reducing environmental degradation. (Bélaïd & Youssef, 2017) examined the role of renewable and non-renewable electricity consumption on environmental degradation in Algeria from 1980 to 2012. They found that economic growth and non-renewable electricity consumption drive environmental degradation, while renewable energy has a positive but limited effect on reducing CO2 emissions. (Ummalla et al., 2019) analyzed the relationship between hydroelectric energy consumption, economic growth, and CO2 emissions in BRICS countries from 1990 to 2016, finding that hydroelectric energy promotes economic growth and reduces CO2 emissions. (Kirikkaleli & Adebayo, 2021) explored the long-term effects of financial development and renewable energy consumption on environmental sustainability, finding that both factors positively impact sustainability globally.

(Xu et al., 2020) investigated the relationship between economic growth, biofuel consumption, urbanization, and CO2 emissions in seven selected G20 countries from 2001 to 2017. Their findings confirmed the EKC hypothesis and revealed that biofuel consumption reduces CO2 emissions, while urbanization increases them. (Salari et al., 2021) examined the relationship between CO2 emissions, renewable and non-renewable energy consumption, and economic growth across US states from 1997 to 2016, finding that non-renewable energy consumption increases CO2 emissions, while renewable energy consumption decreases them. (O. Usman et al., 2022) assessed the effects of domestic material consumption, renewable energy consumption, and financial development on environmental quality in 28 EU countries from 2000 to 2017, highlighting the positive impacts of financial development and renewable energy on environmental quality.

(Magazzino et al., 2022) found that renewable energy consumption reduces CO2 emissions without negatively affecting economic growth in Scandinavian countries from 1990 to 2018. (Yu et al., 2022) showed that solar energy consumption reduces CO2 emissions across various quantiles in the top ten solar energy-consuming countries from 1991 to 2018. (Waris et al., 2023) indicated that solar energy and biofuel consumption negatively impact carbon emissions in G20 countries from 2000 to 2019, while coal consumption has the opposite effect. (Namahoro et al., 2023) found that wind energy consumption contributes to reducing CO2 emissions, while industrial and economic development increase emissions in 41 leading wind energy-producing countries from 1997 to 2018.

(M. Hussain et al., 2023) examined the role of economic policies, renewable energy consumption, and natural resources in reducing carbon emissions in the world's five largest polluting economies from 1992 to 2020, finding that these factors significantly impact environmental quality.(Pata & Aydin, 2020) tested the EKC hypothesis for the six largest hydropower-consuming countries from 1965 to 2016, finding that hydropower consumption does not mitigate environmental degradation despite contributing to economic growth.(S. Nathaniel & Khan, 2020) analyzed the relationship between urbanization, renewable and non-renewable energy consumption, trade, and environmental footprint in six ASEAN countries from 1990 to 2016, recommending sustainable trade and economic policies. (Sharma et al., 2021) explored the effects of per capita income, renewable energy, life expectancy, and population density on the environmental footprint in eight developing countries in Southeast Asia from 1990 to 2015, supporting the need for low-pollution energy sources.

(Wang, 2021)evaluated the impacts of financial development, human capital, globalization, and renewable energy consumption on environmental and carbon footprints in BRICS countries from 1997 to 2016, emphasizing the need for educational, energy, and trade policies. (M. Usman et al., 2021) investigated the determinants of environmental footprint and economic growth in the top 15 emitting countries from 1990 to 2017, recommending enhancements in renewable energy use and financial policies. Nathaniel et al. (2021) assessed the relationship between natural resources, renewable energy, human capital, and environmental footprint in BRICS countries from 1990 to 2016, highlighting the positive effects of renewable energy and the need for human capital development. (O. Usman et al., 2021) examined the role of economic impact dynamics, renewable energy consumption, and innovation in environmental degradation in G7 countries from 1985 to 2016, confirming the EKC hypothesis and the importance of innovative renewable energy technologies.

(Abid et al., 2022) investigated the impact of renewable energy consumption on the environmental footprint in Saudi Arabia from 1980 to 2017, recommending policies to enhance energy efficiency and renewable energy use. (Miao et al., 2022) explored the role of financial globalization and renewable energy consumption on the environmental footprint in ten industrialized countries from 1990 to 2018, validating the EKC hypothesis and suggesting strategies for integrating renewable energy and financial globalization. (Huang et al., 2022) examined the dynamic correlation between ICT, renewable energy, economic complexity, and environmental footprint in E-7 and G-7 countries from 1995 to 2018, highlighting the need for advanced energy technologies. Finally, (Karlilar & Emir, 2023) found that solar and wind energy consumption positively impact environmental sustainability in India from 1995 to 2018, while coal consumption negatively affects it, recommending an increase in the share of solar and wind energy in India's energy mix.

3. Methodology and Data

This study examines a set of countries, specifically Argentina, Australia, Austria, Belgium, Brazil, Canada, China, Denmark, Finland, France, Germany, Hungary, India, Indonesia, Ireland, Italy, Japan, Malaysia, Netherlands, Norway, Portugal, Singapore, South Africa, Spain, Sweden, Switzerland, Thailand, the United Kingdom, and the United States, over the period from 1990 to 2021. The selection of the sample and the study period is based on data availability. Table 1 provides definitions and sources for the variables used in the study.

Table 1: Study Variables and Data Sources

Symbol	Variable	Unit of Measurement	Source
EFB	**Ecological Footprint Index**	**Measures sustainable development by assessing human consumption demand on the biosphere in global hectares.**	Global Footprint Network
REN	**Total Renewable Energy Consumption**	**Total primary energy consumption from renewable sources (TWh)**	Our World in Data
GDP	**Gross Domestic Product**	**Constant 2010 US dollars**	World Bank World Development Indicators
TRAND	**Trade Openness**	**Percentage of GDP**	World Bank World Development Indicators
KOFGI	**Globalization Index**	**Index**	KOF Globalisation Index
SEC	**Education Level**	**Secondary education enrollment rate**	World Bank World Development Indicators

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The Ecological Footprint variable, which we used as the dependent variable in this study, measures the impact of human activities on the Earth's natural resources. It is an environmental accounting tool that quantifies the amount of nature we have, how much we use, and who uses it (Holmberg et al., 1999). The Ecological Footprint was created in 1992 by Mathis Wackernagel and William Rees at the University of British Columbia. Its purpose is to make sustainability and resource use more comprehensible and accessible to everyone. Essentially, the Ecological Footprint determines the amount of land and water area a population, individual, city, country, or even all of humanity requires to produce the resources it consumes and absorb its waste, using prevailing technology and resource management practices. It is typically measured in global hectares (Kitzes et al., 2007).

For example, if a population's Ecological Footprint exceeds the biocapacity of the area, that area is experiencing an ecological deficit and is said to be living unsustainably(Galli et al., 2014). The Ecological Footprint includes several key components:

- **Carbon Footprint:** This is the most significant part of the ecological footprints of developed countries. The carbon footprint measures the amount of greenhouse gases (primarily carbon dioxide and methane) emitted into the atmosphere through human activities such as burning fossil fuels for electricity, heat, and transportation.
- **Food Footprint:** This is determined by the land required to grow the food (and the trees needed to absorb carbon dioxide emissions from growing this food) we consume. It includes not only the plants we eat but also the plants eaten by the animals we consume.
- **Housing Footprint:** This measures the land area used for living space as well as the energy used to build and maintain these living spaces.
- **Goods and Services Footprint:** This includes all other products and services people consume, such as clothing, electronics, books, musical instruments, sports activities, air travel, and so on.

his study employs the consumption shares of energy from renewable sources, economic growth, the globalization index, education level, and trade openness to determine the impact of renewable energy consumption on the Ecological Footprint. The Ecological Footprint is expressed as follows:

$$\mathbf{EFB_{i,t} = f\left(REN_{i,t} + GDP_{i,t} + KOFGI_{i,t} + SEC_{i,t} + TRADE_{i,t}\right)}$$

After taking the logarithm, the equations can be clearly written as follows:

$$\mathbf{lnEFB_{i,t} = \beta_0 + \beta_1 lnREN_{i,t} + \beta_2 lnGDP_{i,t} + \beta_3 lnKOFGI_{i,t} + \beta_4 lnSEC_{i,t} + \beta_5 lnTRADE_{i,t} + \varepsilon_{i,t}}$$

This equation represents the relationship between the Ecological Footprint (EFB) and various independent variables: Renewable Energy Consumption (REN), Gross Domestic Product (GDP), Globalization Index (KOFGI), Education Level (SEC), and Trade Openness (TRADE), along with the error term $\boldsymbol{\varepsilon_{i,t}}$

A. Cross-sectional Dependency Test:

Cross-sectional dependence is a type of correlation and is one of the common issues that often appear in panel data estimates. It indicates the likelihood that cross-sections in panel data are interrelated. Cross-sectional dependency can result from factors such as spatial effects, omitted common effects, social influences, and economic network interactions (Chudik & Pesaran, 2013).

The properties of first-generation panel unit root tests and cointegration tests assume of cross-sectional independence. The assumption of cross-sectional independence has implications for the estimates obtained and the conclusions drawn because the covariance matrix will increase with the number of cross-sections, leading to unreliable parameter estimates.

We will use the following cross-sectional independence tests:

- **Lagrange Multiplier (LM) Test** (Breusch & Pagan, 1980)

$$\mathbf{LM} = \sum_{i=0}^{N-1} \sum_{j=i+1}^{N} T_{ij}\hat{p}_{ij}^{2} \rightarrow \chi^{2}\frac{N(N-1)}{2}$$

- **Scaled LM Test** (M. H. Pesaran, 2004a)

$$\mathbf{LM_{BC}} = \sqrt{\frac{1}{N(N-1)}}\sum_{i=0}^{N} \sum_{j=i+1}^{N} \left(T_{ij}\hat{p}_{ij}^{2} - 1\right) \rightarrow N(0,1)$$

- **CD Test (M. H. Pesaran, 2004b) :** This is a first-generation test for detecting strong correlation.

$$\mathbf{CD} = \sqrt{\frac{2}{N(N-1)}}\sum_{i=0}^{N} \sum_{j=i+1}^{N} T_{ij}\hat{p}_{ij}^{2} \rightarrow N(0,1)$$

- **Bias-adjusted LM Test** (M. Pesaran et al., 2008)

$$\mathbf{LM_{BC}} = \sqrt{\frac{1}{N(N-1)}}\sum_{i=0}^{N-1} \sum_{j=i+1}^{N} \left(T_{ij}\hat{p}_{ij}^{2} - 1\right) - \frac{N}{2(T-1)} \rightarrow N(0,1)$$

- **CD Test for Weak Cross-sectional Dependence** (M. H. Pesaran, 2015): This is a second-generation test for detecting weak or mild correlation. Pesaran Hashem confirmed that the issue of cross-sectional dependence tends to disappear as both T and N approach infinity, i.e., in large samples.

B. Slope Homogeneity Test:

Another important issue in panel data analysis is testing whether the regression coefficients are homogeneous. In the slope homogeneity test, the null hypothesis assumes that all coefficients are equal, while the alternative hypothesis states that at least one coefficient differs from the others. The Wald test is suitable for both small and large T (Mutascu, 2016) . Similarly, (Swamy, 1970) developed a new homogeneity test after relaxing the assumption of homogeneity. However, this test requires that N be relatively small compared to the time dimension T.

Later, (Hashem Pesaran & Yamagata, 2008) developed a slope homogeneity test for large panel data. The test statistic can be defined as follows:

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

The small sample properties of the $\tilde{\Delta}$ test can be improved under normally distributed errors using the following bias-adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{it})}{\sqrt{var(\tilde{z}_{it})}}\right)$$

However, this test cannot handle the case of heterogeneous and correlated errors. Thus, (Blomquist & Westerlund, 2013) enhanced this test to account for these issues.

C. Panel Unit Root Tests:

First-generation panel unit root tests do not consider cross-sectional independence, leading to biased results (J. Hussain et al., 2020). We will use the so-called second-generation panel unit root tests, which are robust because they account for cross-sectional dependence. Specifically, we will use the CIPS and CADF panel unit root tests to achieve consistent results (M. H. Pesaran, 2007) These tests have the ability to provide reliable and consistent estimates in the presence of cross-sectional independence and/or slope heterogeneity. The test statistic is defined as follows:

$$\mathbf{CADF_i = t_i(N,T) = \left(y_i^T\bar{M}y_{i-1}\right)^{-1}\left(y_{i-1}^T\bar{M} \triangle y_i\right) \Big/ \sqrt{\sigma_i^2\left(y_i^T\bar{M}y_{i-1}\right)^{-1}}}$$

Pesaran developed the Cross-sectional Augmented IPS (CIPS) test by incorporating the Cross-sectional Augmented Dickey-Fuller (CADF) approach. This method improves the panel unit root testing by accounting for cross-sectional dependence and providing more reliable results.

The CIPS test statistic is defined as follows:

$$\mathbf{CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i}$$

where $\mathrm{CADF_i}$ represents the individual Cross-sectional Augmented Dickey-Fuller test statistics for each cross-section i This approach ensures that the test remains robust even in the presence of cross-sectional dependence and slope heterogeneity, making it suitable for large panel datasets.

D. Panel Cointegration Test:

Since traditional panel cointegration tests do not account for cross-sectional dependence, (Westerlund, 2007) developed an error-correction-based cointegration test that is robust even in the presence of cross-sectional dependence. This is generally known as the second-generation panel cointegration test. The basic idea of the test is to examine the absence of cointegration by determining whether error correction exists between the individual panel elements or the entire panel as follows:

$$\mathbf{\Delta Y_{i,t} = \delta'_i d_t + \epsilon_i \left(Y_{i,t-1}\beta'_i X_{i,t-1}\right) + \sum_{j=1}^{p} \varphi_{i,j} Y_{i,j-1} + \sum_{j=0}^{p} \varphi_{i,j} Y_{i,j-1} + \mu_{i,t}}$$

where ϵ_i is the coefficient representing the speed of adjustment toward equilibrium. Westerlund proposed four formulations, including group mean statistics and panel statistics, which are presented in the following equations:

$$\boldsymbol{G_t = \frac{1}{N}\sum_{i=i}^{N} \frac{\epsilon_i}{Se(\hat{\epsilon}_i)}} \qquad \mathbf{G_a = \frac{1}{N}\sum_{i=i}^{N} \frac{T\,\epsilon_i}{\epsilon_i\,(1)}}$$

$$\mathbf{P_t = \frac{\hat{\epsilon}_i}{NSe(\hat{\epsilon}_i)}} \qquad \mathbf{P_a = T\,\hat{\epsilon}_i}$$

These statistics test the null hypothesis of no cointegration by evaluating the presence of error correction mechanisms in the panel data, thus providing robust and reliable results in the presence of cross-sectional dependence.

E. Method of Estimating Quantile Regression (MMQR)

Traditional mean regression estimates may be biased because they use only the conditional mean, which does not capture the full dynamics of the distribution. The method of Moment Quantile Regression (MMQR) proposed by (Machado & Santos Silva, 2019) incorporates individual effects and allows for "heterogeneous conditional covariance effects" of the dependent variable on the entire distribution. It is more suitable when the model includes endogenous explanatory variables, where the individual effects are identified from the panel data.

Furthermore, even if the model is nonlinear, MMQR generates robust estimates in various scenarios. The MMQR technique dominates other nonlinear techniques like the Nonlinear Autoregressive Distributed Lag (NARDL) model. This approach is more accurate even in the presence of outliers and when the error term does not follow a normal distribution (Zhu et al., 2018). Additionally, it accounts for cross-sectional dependence among panel data. The MMQR approach is the most suitable method for dealing with heterogeneity and interaction by integrating both asymmetric and nonlinear links, as it produces non-crossing estimates across structural quantiles.

This method allows the estimation of conditional quantiles through pooled location-scale function estimates. This enables individual effects to influence both the location and scale of the dependent variable and the entire distribution, rather than merely shifting the location. Thus, this method provides information on how heterogeneous conditional covariance effects determine the dependent variable's determinants.

The estimation equation is as follows:

$$Q_{yit}(\tau \mid X_{it}) = a_i(\tau) + X'_{it}\beta(\tau)$$

where:

Q_{yit} is the τ -th quantile of the dependent variable yit given the covariates X_{it}

$a_i(\tau)$ represents the individual effects.

$X'_{it}\beta(\tau)$ denotes the effect of the covariates on the τ -th quantile of the dependent variable.

This equation demonstrates how MMQR provides a comprehensive view of the impact of explanatory variables across different points of the dependent variable's distribution.

F. Heterogeneous Panel Causality Test:

We will use the heterogeneous panel causality test developed by (Dumitrescu & Hurlin, 2012) to detect the causal relationship between variables. The advantage of this test is that it can be used in the case of cross-sectional dependence. Additionally, the test increases the power of the Granger non-causality test even in samples with very small dimensions of T and N. It can also be used for unbalanced panels and performs separate regressions for each cross-sectional data set to find causality (Zaidi , Zafar, & Shahbaz, 2019). The null hypothesis indicates no homogeneous causal relationship in any cross-section, while the alternative hypothesis indicates the presence of a heterogeneous causal relationship in at least one cross-section (Hızarcı & Zeren, 2020). The test statistic is defined as follows:

$$\mathbf{z_{i,t} = a_i + \sum_{j=1}^{p} \beta_i^j z_{i,t-j} + \sum_{j=1}^{p} \gamma_i^j T_{i,t-j}}$$

4. Results and Discussion:

Table 2: Descriptive Statistics for the Variables

Variable	Obs	Mean	Std. dev.	Min	Max
EFB	928	8.171998	0.5728508	7.155969	9.743578
TOT_REN	928	309.057	610.2253	0.271	6545.095

KOFGI	928	75.72665	12.27429	32.01538	91.14088
SEC	928	64.3587	24.25446	35.957	125.8518
TRADE	928	84.14679	67.10161	13.75305	437.3267

The descriptive statistics for the variables highlight significant insights. The average Ecological Footprint (EFB) across the observations is approximately 8.172, suggesting a moderately high demand on the Earth's natural resources, with a standard deviation of 0.573 indicating relatively low variability in EFB values among the countries studied. The EFB ranges from a minimum of 7.156 to a maximum of 9.744, showing that all countries have significant ecological footprints, with some placing notably higher demands on resources.

For Total Renewable Energy Consumption (TOT_REN), the average consumption is 309.057 TWh, indicating a wide range of renewable energy usage among the countries, with a high standard deviation of 610.225 suggesting substantial variability. The range from 0.271 to 6545.095 TWh demonstrates that while some countries have minimal renewable energy usage, others rely heavily on it.

The average Globalization Index (KOFGI) score is 75.727, reflecting a generally high level of globalization among the countries, with a standard deviation of 12.274 showing moderate variability. The values range from 32.015 to 91.141, indicating significant differences in globalization levels, with some countries being less integrated into the global economy.

The average secondary education enrollment rate (SEC) is 64.359%, suggesting moderate to high education levels, with a standard deviation of 24.254 indicating considerable variability. The minimum of 35.957% and maximum of 125.852% reflect that some countries have near-universal secondary education enrollment, while others are significantly lower.

Lastly, the average trade openness (TRADE) is 84.147% of GDP, indicating high levels of trade activity, with a standard deviation of 67.102 highlighting substantial variability. The values range from 13.753% to 437.327%, showing that some countries are highly trade-dependent, while others have relatively low trade activity.

A. Cross-sectional Dependence Test Results

Table 3: Results of Cross-sectional Dependence Tests for Study Variables

Variables	**Lagrange Multiplier LM test**		**Scaled LM test**		**Pesaran (2004) CD test**		**Bias-corrected scaled LM test**		**Pesaran (2015) CD test for weak cross-sectional dependence**	
	CD	**P-Value**	**Statistic**	**P-Value**	**Statistic**	**P-Value**	**CD**	**P-Value**	**CD**	**P-Value**
lnEFB	3069.34	**0.000**	93.4649	**0.000**	13.45	**0.000**	92.947	**0.000**	45.672	**0.000**
LnREN	8439.24	**0.000**	281.911	**0.000**	89.01	**0.000**	281.44	**0.000**	83.455	**0.000**
lnGDP	11022.7	**0.000**	372.575	**0.000**	104.94	**0.000**	372.05	**0.000**	100.241	**0.000**
lnSEC	2871.88	**0.000**	86.53553	**0.000**	18.78	**0.000**	86.01768	**0.000**	36.488	**0.000**
lnKOFGI	11865.9	**0.000**	402.166	**0.000**	108.90	**0.000**	401.682	**0.000**	108.486	**0.000**
lnTRADE	6406.39	**0.000**	210.572	**0.000**	62.69	**0.000**	210.104	**0.000**	60.885	**0.000**

The results of the cross-sectional dependence tests indicate the rejection of the null hypothesis of no cross-sectional dependence at the 1% significance level across all five applied tests. The p-values for all variables (lnEFB, lnREN, lnGDP, lnSEC, lnKOFGI, and lnTRADE) are 0.000, confirming strong cross-sectional dependence.

This suggests that shocks in one country within the study sample can easily be transmitted to other countries. Consequently, the first-generation panel models, which assume cross-sectional independence, are unsuitable for this study due to the significant presence of cross-sectional dependence. This underscores the need for second-generation panel models that account for such dependencies to provide more reliable and accurate estimates.

B. Results of Slope Homogeneity Test

Table 4: Results of Slope Homogeneity Test

Model: $\mathbf{lnEFB_{i,t} = f(lnREN_{i,t} + lnGDP_{i,t} + lnKOFGI_{i,t} + lnSEC_{i,t} + lnTRADE_{i,t})}$		
Tests	**Delta**	**P-Value**
$\tilde{\Delta}$	18.229	**0.000**
$\tilde{\Delta}$ **adj**	20.933	**0.000**

The table above displays the results of the slope homogeneity test. According to the results of both tests, the null hypothesis of homogeneous slopes is rejected at the 1% significance level. This indicates that the regression coefficients are not homogeneous across the cross-sections. Therefore, it is necessary to use panel data techniques that account for both cross-sectional dependence and heterogeneity to obtain reliable and accurate estimates.

C. Results of Panel Unit Root Test

Table 5: Results of Second-generation Panel Unit Root Tests for Study Variables

Variables	**CIPS**				**CADF**			
	Levels		**1ST Différence**		**Levels**		**1ST Différence**	
	Constant	**Constant & Trend**	**Constant**	**Constant & Trend**	**Constant**	**Constant & Trend**	**Constant**	**Constant & Trend**
lnEFB	-1.985	-2.979***	-5.215***	-5.249***	-1.532	-2.596**	-3.958***	-3.874***
LnREN	-2.696***	-3.041***	-5.554***	-5.712***	-2.315***	-2.668**	-4.093***	-4.133***
lnGDP	-2.060	-2.044	-3.561***	-3.632***	-2.015*	-2.039	-2.718***	-2.768***
lnSEC	-1.163	-2.045	-3.746***	-4.085***	-1.272	-2.189	-2.974	-3.349***
lnKOFGI	-2.903	-3.240***	-5.246***	-5.418***	-2.543***	2.939***	-3.971***	-4.151***
lnTRADE	-1.836	-2.131	-4.323***	-4.528***	-2.315***	-2.832***	-3.395***	-3.488***

(***) (**)(*) indicate significance levels of 1%, 5%, and 10%, respectively.

The outputs of Table 5 indicate the results of the second-generation panel unit root tests. According to the CIPS test, the variable for renewable energy usage is stationary at the level, while the remaining variables (Ecological Footprint, Economic Growth, Education Level, Globalization, and Trade Openness) become stationary after taking the first difference. On the other hand, according to the CADF test, the variables for renewable energy usage, globalization, and trade openness are stationary at the level, while the other variables become stationary after taking the first difference. Therefore, the null hypothesis of the presence of a unit root is rejected, and the alternative hypothesis of stationarity at the first difference is accepted for the variables in the study.

D. Results of Panel Cointegration Test

Table 6: Results of Westerlund Cointegration Test

Model: $\mathbf{lnEFB_{i,t} = f(lnREN_{i,t} + lnGDP_{i,t} + lnKOFGI_{i,t} + lnSEC_{i,t} + lnTRADE_{i,t})}$				
Statistic	**Value**	**Z-value**	**P-value**	**Robust P-value**
Gt	-3.094	4.738	**0.000**	**0.000**
Ga	-9.831	1.327	**0.908**	**0.006**
Pt	-18.243	6.637	**0.000**	**0.000**
Pa	-12.222	2.837	**0.002**	**0.000**

The results obtained from the Westerlund tests, as shown in Table 6, indicate the following:

- The Gt and Pt statistics both have robust p-values of 0.000, suggesting strong evidence to reject the null hypothesis at the 1% significance level. This indicates that there is a significant long-term cointegration relationship between the dependent variable, Ecological Footprint, and the explanatory variables in the renewable energy model.
- The Ga statistic has a p-value of 0.908 and a robust p-value of 0.006, which implies mixed results. However, the robust p-value still supports rejecting the null hypothesis.
- The Pa statistic has a p-value of 0.002 and a robust p-value of 0.000, reinforcing the evidence of cointegration.

Overall, the results from the Westerlund cointegration tests (Gt, Ga, Pt, and Pa) provide strong evidence to accept the alternative hypothesis, confirming the presence of a cointegration relationship. This implies that there is a long-term relationship between the Ecological Footprint and the explanatory variables, including renewable energy usage, economic growth, globalization, education level, and trade openness.

E. Results of Quantile Regression Estimation (MMQR)

Table 7: Quantile Regression Estimation Results for the Model on the Impact of Total Renewable Energy Usage on Ecological Footprint

	Model $\mathbf{lnEFB_{i,t} = f(lnREN_{i,t} + lnGDP_{i,t} + lnKOFGI_{i,t} + lnSEC_{i,t} + lnTRADE_{i,t})}$						
	Quantiles	**lnREN**	**lnGDP**	**lnSEC**	**lnKOFGI**	**lnTRADE**	**Cons**
	Location	-0.0435***	0.2879***	-0.3787***	1.0460***	-0.2928***	-1.7224***
	Scale	0.0229***	-0.0017	0.0063	-0.4349***	0.0901***	0.6705***
Lower Quantile	**0.1**	-0.0813***	0.2907***	-0.3891***	1.7650***	-0.4418***	-2.8308***
	0.2	-0.0687***	0.2897***	-0.3856***	1.5252***	-0.3921***	-2.4612***
	0.3	-0.0586***	0.2890***	-0.3829***	1.3331***	-0.3523***	-2.1651***
Middle Quantile	**0.4**	-0.0503***	0.2884***	-0.3806***	1.1763***	-0.3198***	-1.9232***
	0.5	-0.0418***	0.2877***	-0.3782***	1.0138***	-0.2861***	-1.6727***
	0.6	-0.0344***	0.2872***	-0.3762***	0.8742***	-0.2572***	-1.4575***
Quantile Higher	**0.7**	-0.0285***	0.2867***	-0.3746***	0.7621***	-0.2340***	-1.2847***
	0.8	-0.0191*	0.2860***	-0.3720***	0.5822***	-0.1967***	-1.0074***
	0.9	-0.0106	0.2854***	-0.3697***	0.4223**	-0.1635***	-0.7608**

(***) (**)(*) indicate significance levels of 1%, 5%, and 10%, respectively.

The results of the quantile regression estimations indicate that the impact of total renewable energy usage, economic growth, education level, globalization, and trade openness on the ecological footprint varies across different quantiles of the distribution.

- Total Renewable Energy Usage: The negative and statistically significant coefficient across quantiles from 0.1 to 0.8 indicates a significant inverse relationship between total renewable energy usage and the ecological footprint. This implies that an increase in renewable energy usage reduces the ecological footprint. However, this relationship is not statistically significant at the 0.9 quantile.
- Economic Growth: The positive and statistically significant coefficient across all quantiles suggests a significant positive relationship between economic growth and the ecological footprint. This means that an increase in economic growth leads to an increase in the ecological footprint.
- Education Level: The negative and statistically significant coefficient across all quantiles indicates a significant inverse relationship between education level and the ecological footprint. This implies that higher education levels contribute to reducing the ecological footprint.
- Globalization Index: The positive and statistically significant coefficient across all quantiles suggests a significant positive relationship between globalization and the ecological footprint. This indicates that higher levels of globalization lead to an increase in the ecological footprint.
- Trade Openness: The negative and statistically significant coefficient across all quantiles indicates a significant inverse relationship between trade openness and the ecological footprint. This implies that increased trade openness reduces the ecological footprint.

These results demonstrate the varying impacts of the explanatory variables on the ecological footprint across different parts of the distribution, highlighting the importance of considering heterogeneity in the relationships.

F. Results of Heterogeneous Panel Causality Test

Table 8: Results of Heterogeneous Panel Causality Test (Dumitrescu & Hurlin, 2012)

Null Hypothesis	WALL-Stat	Zbar-Stat	P-value	Decision
TOT_REN ≠ > EFB	2.3776	5.2457	0.000	**REN ⇔ EFB**
EFB ≠ > TOT_REN	1.8826	3.3607	0.000	
GDP ≠ > EFB	2.4006	5.3335	0.000	**GDP ⇔ EFB**
EFB ≠ > GDP	1.4854	1.8483	0.000	
SEC ≠ > EFB	2.4335	5.4587	0.000	**SEC ⇔ EFB**
EFB ≠ > SEC	2.4346	3.3146	0.000	
KOFGI ≠ > EFB	1.8399	3.1981	0.001	**KOFGI ⇒ EFB**
EFB ≠ > KOFGI	1.0303	0.1154	0.908	
TRADE ≠ > EFB	3.9608	11.2743	0.000	**TRADE ⇒ EFB**
EFB ≠ > TRADE	1.1039	0.3955	0.692	

The results of the heterogeneous panel causality test reveal significant economic interrelationships among the study variables. The bidirectional causality between renewable energy usage and the ecological footprint underscores the dual influence where increased renewable energy usage reduces environmental degradation, and conversely, environmental awareness drives the adoption of renewable energy. Similarly, the bidirectional causality between economic growth and the ecological footprint suggests that while economic growth tends to increase the ecological footprint due to higher consumption and production, the environmental impact can also feedback into economic policies and growth strategies. The education level's bidirectional relationship with the ecological footprint indicates that higher education promotes better environmental practices, while environmental conditions can influence educational content and priorities. The unidirectional causality from globalization and trade openness to the ecological footprint highlights that increased global integration and trade activities lead to higher environmental impacts, but these impacts do not reciprocally influence globalization or trade practices. These findings suggest that integrated policy measures are essential, considering the mutual dependencies and directional influences to achieve sustainable economic and environmental outcomes.

5. Analysis of Study Results

The study results indicate that increasing the use of renewable energy in industrialized countries significantly reduces the ecological footprint, highlighting its pivotal role in achieving environmental sustainability and promoting a green economy. However, the impact of renewable energy use on the ecological footprint is weaker at higher quantiles (quantile 0.9) due to several factors:

- **Technological Saturation**: At higher quantiles, countries may have reached a saturation point in renewable energy technology use, diminishing the effect of further increases in renewable energy usage.
- **High Economic Growth**: Countries with high economic growth have energy-intensive industrial and commercial activities, making the impact of renewable energy less pronounced in reducing the ecological footprint.
- **Current Infrastructure**: Transitioning to renewable energy requires significant changes in energy infrastructure, which are more complex and costly in countries with high ecological footprints.
- **Institutional and Political Challenges**: Countries with high ecological footprints may face greater challenges in implementing stringent environmental policies and effectively transitioning to renewable energy due to institutional and political obstacles.

The results also show that traditional economic growth increases the ecological footprint, indicating that conventional economic activities negatively impact the environment. This underscores the need for adopting sustainable development policies that minimize the environmental impacts of economic growth, achievable through enhancing renewable energy use and technological innovation.

Furthermore, higher education levels contribute to reducing the ecological footprint by promoting environmental awareness and sustainable practices. Investing in education emerges as an effective strategy for achieving sustainable development and a green economy.

Additionally, the study finds that globalization increases the ecological footprint, while trade openness helps reduce it. These findings emphasize the importance of policies that encourage renewable energy use and investment in education to achieve sustainable development and balance economic growth with environmental conservation.

6. Conclusion:

This study utilized advanced econometric techniques to analyze the impact of the energy transition to renewable energy on promoting the green economy and sustainable development in industrialized countries from 1990 to 2021. Various tests, including cross-sectional dependency tests, slope homogeneity tests, and panel unit root tests, were applied to ensure the accuracy of the data and conclusions.

The results revealed a significant negative relationship between renewable energy use and the ecological footprint, indicating that increasing renewable energy usage reduces environmental emissions and improves environmental quality. However, the positive effects of renewable energy on the ecological footprint are less apparent at higher quantiles. This can be explained by technological saturation, the intensity of economic activities, infrastructure complexity, and institutional and policy challenges in countries with high ecological footprints.

Therefore, the study recommends adopting comprehensive policies that focus on improving energy infrastructure, enhancing technological innovation, and investing in environmental education to maximize the benefits of the energy transition. By doing so, a balance between economic growth and environmental preservation can be achieved, contributing to sustainable development and a green economy in industrialized countries.

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