

## Article

# Revolutionizing Environmental Sustainability: The Role of Renewable Energy Consumption and Environmental Technologies in OECD Countries

Xi Liu <sup>1</sup>, Yugang He <sup>2,\*</sup>  and Renhong Wu <sup>3,\*</sup> <sup>1</sup> School of Business, Jiyang College of Zhejiang A&F University, Zhuji 311800, China<sup>2</sup> Department of Chinese Trade and Commerce, Sejong University, Seoul 05006, Republic of Korea<sup>3</sup> School of Management, Kyung Hee University, Seoul 02447, Republic of Korea

\* Correspondence: 1293647581@jbnu.ac.kr (Y.H.); wurenhongbini@163.com (R.W.)

**Abstract:** This study examines the relationship between economic factors and environmental sustainability in OECD (Organisation for Economic Co-operation and Development) countries from 1990 to 2022, with a particular focus on the impact of renewable energy consumption and environmental technologies on CO<sub>2</sub> emissions. The research utilizes empirical data to establish a clear negative correlation between the adoption of renewable energy sources and the level of CO<sub>2</sub> emissions, highlighting the effectiveness of renewable energy in reducing the environmental impact of economic activities. This finding supports the theoretical perspective that transitioning to cleaner energy sources is vital for achieving environmental sustainability and aligns with the objectives of the OECD's environmental sustainability program. Further analysis reveals a significant negative impact of environmental technologies on CO<sub>2</sub> emissions, underscoring the importance of technological innovation in environmental conservation efforts. The study also explores the dual influence of GDP growth, urbanization, industrialization, and trade on CO<sub>2</sub> emissions, revealing both positive and negative effects across different stages of economic development. Initially, these factors contribute to increased emissions, but as economies mature and integrate more efficient and cleaner technologies, their impact on emissions becomes negative. These findings demonstrate the complex interplay between economic development and environmental sustainability and emphasize the need for policies that encourage renewable energy adoption, support environmental technological innovations, and guide economies towards sustainable practices. The study provides valuable insights for policymakers and stakeholders, advocating for an integrated approach to ensure long-term environmental sustainability in OECD countries.

**Keywords:** renewable energy consumption; environmental technologies; carbon dioxide emissions; environmental sustainability



**Citation:** Liu, X.; He, Y.; Wu, R. Revolutionizing Environmental Sustainability: The Role of Renewable Energy Consumption and Environmental Technologies in OECD Countries. *Energies* **2024**, *17*, 455. <https://doi.org/10.3390/en17020455>

Academic Editors: Antonis A. Zorpas and Michail Tsangas

Received: 12 December 2023

Revised: 10 January 2024

Accepted: 11 January 2024

Published: 17 January 2024



**Copyright:** © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

OECD countries are increasingly grappling with multifaceted environmental challenges that have gained significant attention in recent years. Climate change, biodiversity loss, air and water pollution, and plastic pollution have all become pressing global issues. These challenges have been further compounded by economic shocks and global crises, making it imperative for nations to adopt comprehensive environmental policies. As of January 2023, the OECD's emphasis on green growth underscores the vital need to address these dimensions across various policy domains, including energy, agriculture, industry, and urban development. The complexity of these interrelated challenges demands an integrated and dynamic policy response that carefully balances environmental protection with economic growth and social welfare. Despite the commitments made by OECD countries to take action against climate change, it is concerning that the fiscal cost of supporting fossil fuels nearly doubled in 2022, exceeding USD 1.4 trillion (sourced from the

OECD Inventory of Support Measures for Fossil Fuels 2023). This surge can be attributed in part to geopolitical tensions and efforts to mitigate rising energy costs, revealing the formidable obstacles associated with transitioning from fossil fuels to renewable energy sources. Chu [1], Saqib et al. [2], Dam et al. [3], Behera et al. [4], and Xu et al. [5] have highlighted the critical role of renewable energy and environmental technologies in this context. These technologies offer a promising pathway to reduce dependence on fossil fuels, curb carbon emissions, and promote environmental sustainability. However, realizing this transition requires substantial investment, ongoing innovation, and the implementation of supportive policy frameworks that ensure both effectiveness and equity.

Based on this background, the primary objective of this study is to meticulously analyze the intricate relationship between renewable energy consumption, environmental technologies, and carbon dioxide emissions in OECD countries over a period spanning from 1990 to 2022. This investigation aims to unravel how advancements in renewable energy sources and the adoption of environmental technologies have influenced CO<sub>2</sub> emission patterns in these countries. By exploring this correlation, the study aims to provide significant insights into the effectiveness of renewable energy and environmental technologies as viable tools for reducing carbon emissions. This exploration is particularly crucial for understanding whether the integration of these sustainable solutions can effectively counterbalance the environmental impact of economic development in OECD nations, thereby providing a roadmap for policy formulation and strategic decision-making in the realm of environmental sustainability.

This research contributes to the domain of environmental sustainability by providing an in-depth analysis of the interplay between renewable energy consumption, environmental technology, and CO<sub>2</sub> emissions in the context of OECD countries. The first contribution of this study is its empirical confirmation of a negative correlation between the adoption of renewable energy sources and the level of CO<sub>2</sub> emissions in OECD countries. While the idea that renewable energy can reduce emissions has been discussed by Adebayo and Ullah [6], Voumik et al. [7], Hasni et al. [8], and Saqib and Dincă [9], this study provides concrete, data-driven evidence supporting the effectiveness of renewable energy in mitigating environmental impacts. This empirical finding strengthens the argument for transitioning to cleaner energy sources as a key strategy for environmental sustainability. The second contribution is the study's focus on the impact of environmental technologies on CO<sub>2</sub> emissions. While the importance of technological innovation in environmental conservation has been acknowledged by Alola and Adebayo [10], Huo et al. [11], Cicerone et al. [12], and Albitar et al. [13], this study highlights the significant negative impact of environmental technologies on emissions. This underscores the crucial role of innovation in reducing the environmental footprint of economic activities and adds to the body of knowledge regarding the practical application of technology in environmental sustainability efforts. The final contribution of this study is its analysis of the dual influence of GDP, urbanization, industrialization, and trade on CO<sub>2</sub> emissions over different stages of economic development. This study recognizes that these factors have both positive and negative effects on emissions, depending on the maturity of an economy and its adoption of cleaner technologies. This dynamic perspective on the relationship between economic development and environmental sustainability provides a better understanding of how policy interventions and economic growth stages interact in the context of environmental conservation. In summary, this study contributes to existing literature by providing empirical evidence of the impact of renewable energy adoption and environmental technologies on CO<sub>2</sub> emissions, as well as by offering a dynamic analysis of economic development factors in the context of environmental sustainability in OECD countries. These contributions enhance our understanding of the complex interplay between economic factors and environmental outcomes, providing valuable insights for policymakers and stakeholders working towards sustainable practices in these nations.

The structure of this paper is organized as follows: Section 2 delves into a comprehensive review of existing literature, exploring relevant studies and connecting their findings to

the goals of our research. In Section 3, we detail the methodology, specifically the selection and application of the variables and models used in our analysis. Section 4 presents our research findings and engages in a thorough discussion of the results. Finally, Section 5 synthesizes the key insights derived from our study, presenting our conclusions and discussing their implications for the field of study.

## 2. Literature Review

The relationship between renewable energy and CO<sub>2</sub> emissions is a key focus of recent research. Studies by Huang et al. [14], Omri and Saadaoui [15], and Karakurt and Aydin [16] highlighted the increasing fossil CO<sub>2</sub> emissions, emphasizing the need for renewable energy as a solution. In contrast, research by Gielen et al. [17], Berdysheva and Ikonnikova [18], and Bell [19] showed a shift in global energy trends. They noted a decline in fossil fuel assets and a rise in renewable energy adoption, suggesting a gradual energy transition. Neagu [20], Yao et al. [21], and Arnaut and Lidman [22] explored the relationship between economic growth and CO<sub>2</sub> emissions. They proposed an inverted U-shaped relationship where emissions rose with economic growth until a certain income level, after which they declined. This relationship has been validated in various contexts, showing a complex dynamic between economic development, renewable energy adoption, and CO<sub>2</sub> emissions. The role of energy efficiency was also significant. Wei et al. [23], along with Liu et al. [24] and Ahakwa et al. [25], found that advancements in energy efficiency led to CO<sub>2</sub> emission reductions. However, these advancements varied across regions. Mikuli et al. [26] and Gupta et al. [27] investigated novel CO<sub>2</sub> management strategies. They demonstrated the potential of energy-efficient technologies for capturing and converting CO<sub>2</sub>. Additionally, Ren et al. [28] and Zhang and Liu [29] showed how digitalization can lower emissions by enhancing energy system efficiency. Collectively, these studies suggest a multifaceted path to reducing CO<sub>2</sub> emissions through renewable energy.

Recent literature underscores the critical role of environmental technology in promoting sustainability, focusing on how technological advancements contribute to reducing carbon emissions. The concept of a circular economy is identified as a key decarbonization strategy across industries. Researchers such as Dell'Anna [30], Awasthi et al. [31], and Capodaglio and Olsson [32] emphasized the importance of reducing consumption, increasing efficiency, and recapturing energy for environmental sustainability. Further contributions were seen in the realm of digital technologies. Li et al. [33] and Yang et al. [34] discussed how these technologies enhanced information processing, optimized organizational structures, and improved production processes, thereby significantly impacting carbon emission reduction. In the same vein, Vinuesa et al. [35], Nishant et al. [36], and Galaz et al. [37] showed the potential of artificial intelligence applications in environmental efforts. For example, deep reinforcement learning models have proven effective in manufacturing for addressing carbon emission sources like machine operation energy consumption. Ang et al. [38], Newton and Rogers [39], and Chen et al. [40] demonstrated various carbon reduction technology pathways for buildings in different urban settings. They illustrated how technology could be tailored to specific environments and climate conditions to achieve significant carbon emission reductions. Dong et al. [41], Ma et al. [42], and Yi et al. [43] explored the impact of digital technology on carbon emissions. They found that the digital economy not only fostered economic and industrial transformation but also enabled sustainable societal development, thereby significantly influencing carbon emissions. Here, the efficiency improvements brought by digital technology were central. Urban greening strategies, as discussed by Dorst et al. [44], Fan et al. [45], and Feng et al. [46], further highlight the role of environmental technology in sustainability. These strategies went beyond just capturing carbon to actively reducing it, underscoring the importance of integrating nature-based solutions in urban planning. Lastly, Stern and Valero [47] and Bataille [48] emphasized that net-zero technologies were essential in reducing carbon emissions. These innovative solutions were integral to achieving substantial emissions reductions and were increasingly being integrated into various sectors. In summary, these

studies collectively underscore the indispensable role of environmental technologies in reducing carbon emissions and advancing sustainable practices.

Current scholarly works examine the link between various economic indicators, like increases in GDP, the expansion of urban areas, the progression of industrial activities, and commercial exchanges, and their contrasting effects on the health of the environment, with a special emphasis on the implications for carbon dioxide release. Chou et al. [49] revealed a notable trend despite the global increase in fossil CO<sub>2</sub> emissions: emissions may soon peak due to factors including economic growth. This suggests a complex scenario where initial economic growth leads to increased emissions, but over time, as economies mature, they may reduce emissions by adopting cleaner technologies. Delving deeper, Favero et al. [50] and Sadiq et al. [51] used the global timber model and other system frameworks to demonstrate the significant impact of economic drivers on bioenergy carbon debts and climate policies. They stressed the importance of considering both market dynamics and terrestrial carbon responses to forest biomass consumption, highlighting the interplay between physical and economic systems. Anwar et al. [52], Pu et al. [53], and Zhang et al. [54] have all studied the impact of urbanization on CO<sub>2</sub> emissions. They found that cities experiencing rapid area growth tend to see increases in per capita CO<sub>2</sub> emissions, providing direct evidence of the impact of changing urban forms on emissions and underscoring the importance of considering urbanization patterns in sustainability efforts. Mardani et al. [55], Magazzino et al. [56], Farahzadi and Kioumarsi [57], and Magazzino and Mele [58] identified economic scale, structure, and technological level as major factors influencing environmental quality. They noted that economic growth, which requires more resources and energy, often leads to increased pollution. However, Chen and Taylor [59], Cansino et al. [60], and Zhang et al. [61] found that as economies develop, changes in industry structure and technological advancements can mitigate pollution, illustrating the environmental Kuznets curve hypothesis. Wang et al. [62] and Wu et al. [63] observed that in developing countries, rapid economic growth initially increases energy consumption and carbon emissions, mainly through fossil fuels and crude oil. This growth leads to increased air pollution, but beyond a certain economic threshold, these countries begin controlling carbon emissions by adopting cleaner energy sources. This aligns with the EKC hypothesis, where environmental impact initially increases with economic growth but decreases as further development occurs. In summary, these studies collectively indicate that while economic growth, urbanization, industrialization, and trade initially contribute to increased carbon emissions, they also play a crucial role in driving the adoption of sustainable practices and technologies, ultimately leading to emission reductions. As a result, the relationship between these economic factors and environmental sustainability is complex and changes over time as a result of policy changes, technological advancements, and economic development.

In examining the adoption of renewable energy and technological innovation in OECD countries, this paper uncovers significant insights and identifies existing research gaps. Studies by Ahmed et al. [64], Sharif et al. [65], Paramati et al. [66], and Mensah et al. [67] highlighted the progress in enhancing green energy supply and environmental sustainability through investments in green energy technology within these nations. Their findings reflected a broader trend in OECD countries towards prioritizing sustainable energy sources and innovative technologies to address environmental challenges. However, the research landscape shows notable gaps. Chakraborty and Mazzanti [68], Gozgor et al. [69], Samant et al. [70], Zhao et al. [71], and Saqib et al. [72] pointed out that while there was a significant shift towards renewable energy and technological innovation, there was a need for more comprehensive research. This further research should explore the broader implications of these changes, particularly their impact on environmental economics in the OECD context. This analysis highlights the importance of our study in addressing these gaps, aiming to enhance the understanding of environmental sustainability development in OECD countries.

### 3. Variable and Model

#### 3.1. Variable

**Dependent variable:** In environmental and energy economic discourse, carbon dioxide emissions' significance as an indicator of environmental sustainability in OECD countries is increasingly recognized by contemporary research. Bashir et al. [73] explored the interplay between economic factors, environmental aspects, and CO<sub>2</sub> emissions, highlighting how policy and institutional quality could influence emission trajectories in OECD nations. Additionally, Ulucak et al. [74] examined the impacts of environmental taxes and technology on carbon emissions, demonstrating the potential of fiscal and technological interventions to reduce emissions within these economies. Mardani et al. [75] emphasized the relationship between economic growth and CO<sub>2</sub> emissions, suggesting that policies must balance economic development with emission reduction. Furthermore, Iram et al. [76] focused on energy and environmental efficiency in OECD countries, revealing the crucial role of energy efficiency in reducing carbon emissions and indicating that improvements in this area could significantly enhance environmental sustainability. Collectively, these studies affirm the multifaceted implications of CO<sub>2</sub> emissions in assessing and guiding sustainability efforts in OECD countries, integrating economic, policy, technological, and efficiency perspectives. Therefore, this article uses CO<sub>2</sub> emissions as a proxy for environmental sustainability.

**Independent variable:** Numerous studies support the link between renewable energy use, environmental technologies, and carbon dioxide emissions as key indicators of environmental sustainability in OECD countries. Mirziyoyeva and Salahodjaev [77] focused on highly globalized countries, including several OECD members, establishing a significant negative correlation between renewable energy usage and CO<sub>2</sub> emissions. This supports the effectiveness of renewable energy in reducing emissions and illustrates the inverted U-shaped relationship between GDP and CO<sub>2</sub> emissions, aligning with the environmental Kuznets curve hypothesis. Concurrently, Tariq et al. [78] highlighted the substantial impact of green technology and energy efficiency in reducing greenhouse gas emissions in South Asian contexts. This finding could be extrapolated to OECD countries due to their technological and economic similarities. Moreover, the emergence of the 4th Industrial Revolution underscores the role of technological innovation in mitigating environmental impacts. Lasisi et al. [79] demonstrated that eco-innovation and the development of green technologies are instrumental in lowering CO<sub>2</sub> emissions in various developed economies. Razzaq et al. [80] emphasized energy efficiency as a key tool for climate change mitigation, noting that energy-efficient practices effectively reduce greenhouse gas emissions, a principle applicable to OECD economies striving for sustainable development. Therefore, in this article, renewable energy consumption and environmental technologies are used as independent variables.

**Control variable:** In this analysis, to enhance the accuracy of assessing the impact of renewable energy consumption and environmental technologies on CO<sub>2</sub> emissions, we incorporate several control variables, guided by key literature in the field. Following He et al. [81], we integrate gross domestic product as a critical economic variable, recognizing its potential influence on energy consumption patterns and technological adoption. Building upon the insights of He [82] and Kang [83], trade is included as a variable to acknowledge its role in shaping energy demands and facilitating the transfer of environmental technologies. The factor of urbanization, drawn from the studies of Wang et al. [84] and He [85], is considered to account for demographic shifts and their corresponding effects on energy use and CO<sub>2</sub> emissions. Lastly, the dimension of industrialization, following the approaches of Wu and Xie [86] and Wang and He [87], is introduced to assess its interplay with renewable energy consumption and environmental technological advancements. This comprehensive inclusion of control variables aims to provide a better understanding of the determinants affecting CO<sub>2</sub> emissions in the context of renewable energy and environmental technology usage.

To provide a clearer understanding of the variables used in this study, their key characteristics and details are summarized in Table 1.



**Table 1.** Results of variable description.

Variable	Form	Definition	Source
Carbon dioxide emissions	co	Carbon dioxide emissions (kt) in log	World Bank
Renewable energy consumption	re	Renewable energy consumption (% of total final energy consumption)	World Bank
Environmental technologies	en	Patents on environmental technologies in log	OECD data
Gross domestic product	gr	GDP (constant 2015 USD) in log	OECD data
Trade	tr	Ratio of the total trade to GDP	OECD data
Urbanization	ur	Share of the urban population in the total population	OECD data
Industrialization	in	Ratio of industry to GDP	OECD data

### 3.2. Model

#### 3.2.1. Theoretical Model

Numerous scholarly inquiries have explored the relationship between anthropogenic activities and CO<sub>2</sub> emissions, utilizing models such as IPAT (Impact, Population, Affluence, Technology), STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology), and the Kaya identity. Recognizing the limitations of the IPAT model, which assumes proportionality among its variables, York et al. [88] introduced the STIRPAT model. This model offers a more nuanced approach, enabling a more comprehensive analysis of the varied impacts of human activities on the environment. In line with the STIRPAT framework, this study designates CO<sub>2</sub> emissions as the dependent variable, with renewable energy consumption and environmental technologies as the independent variables. This approach seeks to elucidate the connections between CO<sub>2</sub> emissions, renewable energy, and environmental technology. Accordingly, this research employs a geographically oriented panel measurement model incorporating these three variables. A review of the existing literature such as Van Le et al. [89], He [90], Liao et al. [91], and Lee and Zhao [92] informs the inclusion of four additional control variables—gross domestic product, trade, urbanization, and industrialization—to enhance the model’s robustness. The theoretical foundation of this methodology led to the development of the following model in this study:

$$co_{i,t} = f(re_{i,t}, en_{i,t}, gr_{i,t}, tr_{i,t}, ur_{i,t}, in_{i,t}). \quad (1)$$

The derived regression model, as delineated in Equation (1), is presented as follows:

$$co_{i,t} = a_0 + a_1 re_{i,t} + a_2 en_{i,t} + a_3 gr_{i,t} + a_4 tr_{i,t} + a_5 ur_{i,t} + a_5 in_{i,t} + \epsilon_{i,t}. \quad (2)$$

In Equation (2), *i* represents the variable denoting the country, and *t* signifies the temporal dimension, namely the year. *a*<sub>0</sub> is indicative of the constant term in the regression equation. [*a*<sub>1</sub>, *a*<sub>5</sub>] are the parameters to be estimated within the model framework. Lastly,  $\epsilon$  denotes the stochastic error term, often referred to as white noise, which captures the unexplained variability in the regression model.

#### 3.2.2. Econometric Model

In the preliminary phase of this research, descriptive statistical methods are used to effectively summarize the dataset before conducting empirical analyses. These statistics primarily delineate the key characteristics of the dataset, which include measures of central tendency (such as mean and mode), measures of variability (such as range and standard deviation), and the distribution frequency of the data points. Furthermore, this study employs the Jarque–Bera test, as proposed by Jarque and Bera [93], to assess the normality of the data distribution. The Jarque–Bera test evaluates whether the data sample is consistent

with a normally distributed population, calculating the test statistic according to the formula established in their study.

$$JB_{\text{test}} = \frac{N}{6} \left( S^2 + \frac{(K-3)^2}{4} \right). \quad (3)$$

Within the framework of Equation (3),  $N$  represents the total number of observations under analysis.  $S$  is an indicator of the skewness of the data, while  $K$  symbolizes excess kurtosis. Once the test statistic has been calculated, it is compared to a chi-square distribution with two degrees of freedom in order to find the accompanying  $p$ -value. In cases where this  $p$ -value falls below the predetermined threshold for significance (for example, 0.05), it leads to the rejection of the null hypothesis, which posits that the dataset follows a normal distribution.

In this study, we analyze specific characteristics of panel data, focusing on aspects such as slope coefficient heterogeneity and panel cross-section dependence. Slope coefficient heterogeneity refers to variations in the slope coefficients across different entities or groups within the panel dataset, while panel cross-section dependence indicates the existence of interdependencies among various units or groups in the panel. Both of these factors are critical, as they can potentially lead to biased or inefficient results in panel data regression analyses. To address these concerns, the present research employs the Pesaran and Yamagata [94] test for slope coefficient heterogeneity. This test provides both a standard assessment and an adjusted version of slope coefficient heterogeneity, represented by the following formulas:

$$\Delta_{\text{sch}}^{\check{v}} = \left( \frac{1}{N(2k)} \right)^{\frac{1}{2}} \left( \frac{S}{N} - K \right). \quad (4)$$

$$\Delta_{\text{asch}}^{\check{v}} = \left( \frac{1}{N} \right)^{\frac{1}{2}} \left( \frac{T+1}{2K(T-K-1)} \right)^{\frac{1}{2}} \left( \frac{S}{N} - 2K \right). \quad (5)$$

In the equations presented,  $\Delta_{\text{sch}}^{\check{v}}$  symbolizes the homogeneity of the slope coefficient as per the initial formulation, whereas  $\Delta_{\text{asch}}^{\check{v}}$  represents the adjusted homogeneity of the slope coefficient in the subsequent equation. Furthermore, the null hypothesis of the above test assumes that the slope coefficients are the same across the panel data. This hypothesis will remain valid until the calculated statistics go above the established level of statistical significance.

Globalization, cross-border competitiveness, and international trade promote specialization in specific goods and services with global demand, leading to increased interdependence among nations focusing on these specializations. In this context, to detect interdependencies within panel data sets, Pesaran [95] developed the cross-sectional dependence test. This test calculates its statistic by averaging the correlation coefficients across sectional units, derived from the residuals of a panel regression model. The formulation of the cross-sectional dependence test statistic is as follows:

$$CD_{\text{test}} = \left( \frac{2T}{N(N-1)} \right)^{\frac{1}{2}} \sum_{i=1}^{N-1} \cdot \sum_{k=i+1}^N T_{i,k}. \quad (6)$$

The cross-sectional test statistic asymptotically follows a standard normal distribution under the null hypothesis, which posits no cross-sectional dependence. To assess the null hypothesis's validity, this test statistic is compared with the critical values from the standard normal distribution. This comparison is used to determine the appropriateness of rejecting the null hypothesis.

To address the challenges of slope coefficient heterogeneity and panel cross-section dependence in panel data, this study employs an appropriate unit root estimator. Specifically, it adopts the CIPS unit root test for panel data, introduced by Pesaran [96]. This test operates on the premise that while the panel data may be non-stationary overall, individual series within it might be stationary. The test statistic is calculated by averaging the unit root test statistics from the individual series. Under the null hypothesis, which posits no

unit root, this statistic is asymptotically distributed as a standard normal. The computation of the CIPS unit root test statistic is as follows:

$$\Delta y_{i,t} = \theta_i + \beta_i^* \tilde{y}_{i,t-1} + d_0 y_{t-1} + d_1 \Delta \tilde{y}_t + \epsilon_{i,t}. \quad (7)$$

In Equation (7),  $\tilde{y}_t$  represents the average value across the total number of observations. To accommodate potential serial correlation within the data, this equation can be extended. This extension involves the incorporation of the first differenced lags of  $\tilde{y}_t$  and  $y_{i,t}$ , which are articulated in the subsequent formulation:

$$\Delta y_{i,t} = \theta_i + \beta_i^* \tilde{y}_{i,t-1} + d_0 y_{t-1} + \sum_{j=0}^n d_{j+1} \Delta \tilde{y}_{t-j} + \sum_{k=1}^n c_k \Delta y_{i,t-k} + \epsilon_{i,t}. \quad (8)$$

The calculated statistic of the test is compared against critical values from the standard normal distribution. This comparison plays a crucial role in determining whether it is feasible to reject the null hypothesis, which asserts that there is no unit root in the data set.

In this analysis, we apply the error correction framework developed by Westerlund [97] to explore the long-term equilibrium relationship among variables within the OECD economies. This particular approach is adept at identifying cointegration within panel datasets that exhibit interdependencies across individual time series. Central to this test is the premise that, while the overall panel dataset might display non-stationarity, the individual time series within it are cointegrated. For a comprehensive examination of both group and panel-level dynamics, this method incorporates the assessment of group mean statistics through  $G_\tau = \frac{1}{N} \sum_{i=1}^N \frac{\tilde{a}_i}{S.E \tilde{a}_i}$  and  $G_a = \frac{1}{N} \sum_{i=1}^N \frac{T \tilde{a}_i}{\tilde{a}_i(1)}$ , and panel estimates through  $P_\tau = \frac{\tilde{a}}{S.E \tilde{a}}$  and  $P_a = T \cdot \tilde{a}$ .

Koenker and Bassett Jr. [98] were the pioneers in introducing panel quantile regression. This approach uses regressor values to estimate the conditional distribution of the dependent variable, not just its mean and conditional variance. It is especially useful for analyzing datasets with inconsistent distribution patterns. The current study adopts the innovative method of moments quantile regression, developed by Machado and Silva [99], to tackle distribution irregularities. This advanced technique is utilized to examine the redistributive and diversification properties of the quantile values. The mathematical formulation of the method of moments quantile regression is outlined as follows:

$$Y_{i,t} = a_i + \beta R_{i,t} + (\gamma_i + \rho \tilde{Z}_{i,t}) \epsilon_{i,t}. \quad (9)$$

Equation (9) posits that the probability  $(\gamma_i + \rho \tilde{Z}_{i,t} > 0)$  is equal to one. The coefficients estimated within this framework are denoted as  $\alpha$ ,  $\beta$ ,  $\gamma$ , and  $\rho$ . Moreover, the subscript  $i$  in  $\alpha_i$  and  $\gamma_i$  signifies the fixed effects for each entity in the panel, where  $i$  ranges from 1 to  $n$ . Additionally, the  $k$  – vector refers to the fundamental element of the real number space  $\mathbb{R}$ , which is  $\mathbb{Z}$ . In contrast, the symbol  $m$  represents a unique variation, articulated as follows:

$$Z_1 = Z_m(\mathbb{R}), m \in [1, k]. \quad (10)$$

According to Machado and Silva [99],  $R_{i,t}$  is independently and symmetrically distributed for each specified entity ‘ $i$ ’ and time point ‘ $t$ ’, as well as being orthogonal to both ‘ $i$ ’ and ‘ $t$ ’. This distribution pattern contributes to the stabilization of external factors and the conservation of reserves. Consequently, Equation (2) can be reformulated as follows:

$$Q_y(\tau | R_{i,t}) = [a_i + \gamma_i q(\tau)] + \beta R_{i,t} + \rho \tilde{Z}_{i,t} q(\tau). \quad (11)$$

The aforementioned equation illustrates that  $R_{i,t}$  encapsulates a vector comprising all the explanatory variables, encompassing  $re_{i,t}$ ,  $en_{i,t}$ ,  $gr_{i,t}$ ,  $tr_{i,t}$ ,  $ur_{i,t}$ , and  $in_{i,t}$ . Additionally,  $R_{i,t}$  is indicative of the quantile distribution for  $Y_{i,t}$ , which is representative of CO<sub>2</sub> emissions



and varies by location. Moreover,  $-a_i(\tau) \equiv a_i + \gamma_i q(\tau)$  serves as a scalar coefficient that embodies the fixed impact of the  $\tau$  quantiles on the variable  $i$ .

While the method of moments quantile regression provides estimations for each predictor at specified locations and scales, it falls short in revealing the causal dynamics between explanatory and dependent variables. To bridge this gap, this analysis integrates the Granger panel causality heterogeneity test, developed by Dumitrescu and Hurlin [100]. This test is designed to determine causal relationships within individual time series of a panel dataset with cross-sectional interdependencies. Its fundamental assumption is the non-stationarity of panel data, where each series of order one is integrated. Recognizing the limitations of previous estimators, this research employs the panel quantile regression method, originally introduced by Koenker and Bassett Jr. [98]. This methodology extends the standard quantile regression framework to accommodate this type of data, allowing for the computation of quantile regression models that account for temporal interdependencies among observations. It involves computing distinct quantile regression models for each panel entity, then aggregating these individual estimates for an overall quantile regression analysis.

## 4. Results and Discussion

### 4.1. Basic Statistical Analysis

The objective of this subsection is to conduct a fundamental statistical analysis of the variables presented in the research paper. This involves a series of rigorous statistical tests and a thorough description of the variables under investigation. The tests include evaluating slope heterogeneity, assessing cross-section dependence, conducting a unit root test to determine the stability of the variables, and performing a cointegration test to explore their long-term relationships. The outcomes of these analyses are systematically compiled and presented in Table 2.

The findings presented in Panel A show that the mean values of all examined variables are positive, indicating a consistent upward trend across the dataset. These mean values symbolize the average performance of the variables during the assessment period and encapsulate the temporal challenges within OECD nations. The standard deviation, reflecting temporal volatility, reveals carbon dioxide emissions as the most volatile variable, with a standard deviation of 0.366. Following this, the variables from renewable energy consumption to industrialization have respective standard deviations of 0.107, 0.226, 0.185, 0.284, 0.267, and 0.194. Generally, a higher standard deviation indicates greater variability in the dataset, while a lower value suggests consistency. The data show relatively modest variation among the variables across different OECD countries, possibly due to similar policies on carbon emissions and economic growth. Moreover, the skewness and kurtosis of these variables differ from their theoretical values of 1 and 3, indicating a deviation from a normal distribution. The Jarque–Bera test, used to assess distribution characteristics, yielded highly significant probabilities, leading to the rejection of the null hypothesis of a normal distribution and the conclusion that the variables follow a non-normal distribution.

After gathering descriptive statistics and assessing the normality of the data, the research progresses to analyze panel heterogeneity coefficients and cross-sectional dependency. Prior to determining the specific impacts exerted by the independent variables on carbon dioxide emissions, it was essential to address these panel data concerns. Neglecting such considerations could result in conclusions that are both misleading and unreliable, as indicated in the studies by Breitung [101], Yang et al. [102], and Ma et al. [103]. To this end, Panel B presents the results of the slope heterogeneity test, conducted using the methodology developed by Pesaran and Yamagata [94]. The analysis of these results reveals that the coefficients labeled  $\Delta_{sch}$  and  $\Delta_{asch}$  are statistically significant at a 1% level. Consequently, the hypothesis asserting homogeneity of slope coefficients is not tenable. Therefore, it can be concluded with confidence that the slope coefficients exhibit heterogeneity across the panel data.

Table 2. Results of basic statistical analysis.

Panel A: Variable Description							
V and S	Mean	Maximum	Minimum	Std	Skewness	Kurtosis	J-B
co	5.376	6.127	5.031	0.366	1.627	2.143	98.242 ***
re	0.465	0.584	0.329	0.107	1.057	3.806	70.522 ***
en	2.126	3.761	1.038	0.226	−0.627	2.318	81.059 ***
gr	12.246	13.051	11.742	0.185	−0.159	1.576	58.861 ***
tr	0.567	0.419	0.263	0.284	−0.436	3.859	61.609 ***
ur	0.787	0.928	0.475	0.267	−0.568	3.689	92.252 ***
in	0.747	0.8328	0.5018	0.194	1.026	2.676	66.974 ***
Panel B: Slope heterogeneity test							
	$\Delta_{sch}$					$\Delta_{asch}$	
	19.499 ***					21.862 ***	
Panel C: Cross-section dependence test							
V and S	co	re	en	gr	tr	ur	in
	12.144 ***	22.535 ***	29.248 ***	29.377 ***	30.663 ***	19.022 ***	14.483 ***
Panel D: Unit root test							
V and M	Level			1st level		Result	
co	3.248 ***			7.043 ***		I(0); I(1)	
re	2.706 *			4.752 ***		I(0); I(1)	
en	1.864			6.196 ***		I(1)	
gr	3.629 ***			4.664 ***		I(0); I(1)	
tr	1.715			6.927 ***		I(1)	
ur	1.415			5.722 ***		I(1)	
in	1.651			6.157 ***		I(1)	
Panel E: Cointegration test							
	$G_{\tau}$	$G_a$	$P_{\tau}$	$P_a$			
	−11.209 ***	−26.968 ***	−22.075 ***	−30.526 ***			

Note: V variable; S statistics; M method; Std standard deviation; J-B Jarque–Bera statistics; \* a 10% significant level; \*\*\* a 1% significant level.

Beyond addressing issues of panel data, Panel C delineates the results of the panel cross-section dependence test, conducted in accordance with Pesaran’s [95] methodology. The empirical evidence from this test indicates that variables such as co, re, en, gr, tr, ur, and in exhibit statistical significance. This leads to the rejection of the hypothesis asserting independence among cross-sections, thereby affirming the presence of cross-sectional dependence within OECD economies. This dependence is likely due to various factors that interlink economies, compelling them to rely on one another to achieve diverse goals. In particular, the OECD, being a prominent industrial and economic region, demonstrates a high degree of interconnectedness. The substantial income levels and investment activities in these economies generate demand, which is often met through international trade, further reinforcing cross-sectional dependence. Given the presence of both panel heterogeneity and cross-sectional dependence in the data, this research adopts a suitable methodological approach for analyzing stationarity, taking these factors into consideration.

Panel D outlines the results derived from employing the Pesaran [96] CIPS test for unit roots. The analysis reveals that variables such as carbon dioxide emissions, renewable energy consumption, and GDP exhibit statistical significance at the I(0) level at both 1% and 10%, suggesting their stationarity over time. Conversely, variables including environmental technologies, trade, urbanization, and industrialization are found to contain a unit root, indicating non-stationarity in their original form. To address this, these variables are subsequently examined in their first-differenced forms. Post-transformation, these latter variables demonstrate statistical significance at the 1% level. This allows for the rejection of the null hypothesis pertaining to the presence of a unit root in these variables,

confirming their stationarity post-difference. This verification of stationarity paves the way for investigating the long-term cointegration relationships among the variables in question.

The debate among economists regarding the occurrence and implications of cross-sectional dependence and slope heterogeneity remains a pertinent topic, particularly in the context of OECD countries. Cross-sectional dependence implies that fluctuations in one economic parameter (such as GDP) are often influenced by changes in other parameters (like CO<sub>2</sub> emissions). In contrast, slope heterogeneity suggests that different regions within a country exhibit distinct growth or production trajectories. This divergence in regional growth patterns can lead to competitive disadvantages for certain areas, potentially reducing overall economic efficiency and growth. Given that the studied variables display a mix of integration orders, being stationary at both I(0) and I(1) at varying levels of significance, this research applies the Westerlund [97] error correction model approach to explore the cointegration relationships among these variables. The empirical findings from this test are presented in Panel E. According to Westerlund [97], the error correction term should be zero. However, the analysis reveals that both the group mean ( $G_{\tau}$  and  $G_a$ ) and panel ( $P_{\tau}$  and  $P_a$ ) statistics are statistically significant at the 1% level. This leads to the dismissal of the null hypothesis, suggesting a non-zero error correction term. Therefore, it can be deduced that variables such as *co*, *re*, *en*, *gr*, *tr*, *ur*, and *in* maintain a long-term equilibrium relationship.

#### 4.2. The Effects of Renewable Energy Consumption and Environmental Technologies on Carbon Dioxide Emissions

In light of the established long-term cointegration relationship among the variables, this research is well-equipped to investigate the specific impact of various regressors on CO<sub>2</sub> emissions. For this, the study employs the Machado–Mata quantile regression method, as described by Machado and Silva [99]. This methodological choice is apt, especially considering the Jarque–Bera test results, which suggest that the variables do not follow a normal distribution pattern. Accordingly, the Machado–Mata quantile regression approach, adept at handling data with non-standard distribution patterns, is employed for the analysis. The results obtained using this method are systematically detailed in Table 3.

**Table 3.** Results of the effects of renewable energy consumption and environmental technologies on carbon dioxide emissions.

Variable and Model	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	Location	Scale	Q <sub>0.25</sub>	Q <sub>0.50</sub>	Q <sub>0.75</sub>	Q <sub>0.90</sub>
re	−0.163 *** (−6.788)	0.078 (1.238)	−0.183 *** (−6.915)	−0.154 *** (−6.807)	−0.115 *** (−6.536)	−0.093 *** (−6.518)
	−0.058 *** (−4.364)	0.019 (1.062)	−0.059 *** (−4.137)	−0.057 *** (−3.992)	−0.055 *** (−3.962)	−0.051 *** (−3.905)
en	0.883 *** (3.397)	−0.032 (−1.134)	0.899 *** (3.398)	0.862 *** (3.295)	0.823 *** (3.201)	0.805 *** (3.002)
	−0.267 ** (−2.201)	0.031 * (1.925)	−0.279 *** (−2.851)	−0.232 *** (−2.772)	−0.211 *** (−2.747)	−0.198 ** (−2.046)
gr	0.443 *** (3.738)	−0.056 *** (−2.659)	−0.453 *** (−3.846)	0.439 ** (2.008)	0.422 ** (2.054)	0.401 * (1.808)
	0.533 ** (2.049)	0.078 (1.066)	−0.547 ** (−2.013)	0.522 * (1.747)	0.518 * (1.623)	0.499 (1.514)
ur	−2.731 * (−1.785)	−0.018 (−1.146)	−2.863 * (−1.776)	−2.451 * (−1.189)	−2.079 (−1.136)	−1.956 (−1.021)

Note: c constant; t-statistical value shown in parentheses; \*\*\* a 1% significant level; \*\* a 5% significant level; \* a 10% significant level.

The findings presented in Table 3 show a negative correlation between renewable energy consumption and CO<sub>2</sub> emissions within OECD countries. This supports the theoretical view that renewable energy, with its low carbon footprint, plays a pivotal role in reducing

environmental impact. The data underline the importance of adopting renewable energy sources over conventional fossil fuels in cutting greenhouse gas emissions. This aligns with sustainable development and environmental economics principles, advocating for a shift to cleaner energy sources to achieve environmental sustainability. In OECD countries, moving towards renewable energy signifies a mature stage of economic development where environmental quality is incorporated into the growth model. Scholars like Pata [104], Cui et al. [105], Caglar et al. [106], and Xue et al. [107] support this, emphasizing advanced economies' role in leading the transition towards sustainable energy practices, thereby reducing their ecological footprint. The analysis shows a consistent negative correlation between environmental technologies and CO<sub>2</sub> emissions across all quantiles, indicating a significant inverse effect. This suggests that advancements in environmental technology are key to promoting sustainability. Such technologies include energy-saving methods, enhancing energy efficiency, and adopting eco-friendly energy sources like renewable energy, reducing reliance on fossil fuels. These findings are echoed in studies by Chen et al. [108], Christoforidis and Katrakilidis [109], Karmaker et al. [110], Khan et al. [111], Fujii and Managi [112], Xu et al. [113], and Cai et al. [114], highlighting the significant negative impact of environmental technologies on emissions in various countries and economic groups. The consistency of these findings across different contexts and methodologies not only validates the current study's observed relationship but also highlights the critical role of technological innovation in environmental conservation efforts.

In the context of OECD countries, the analysis delineates that gross domestic product, urbanization, industrialization, and trade exert both positive and negative influences on CO<sub>2</sub> emissions across all quantiles. This dichotomous impact reflects the dynamics between economic development and environmental sustainability. GDP growth, a proxy for economic activity, is known to initially escalate CO<sub>2</sub> emissions due to increased industrial and energy activities. This relationship is substantiated by these studies of Zafar et al. [115], Odugbesan and Rjoub [116], and Anser et al. [117], which highlight the direct correlation between economic expansion and CO<sub>2</sub> emissions in developed economies. However, as economies evolve, they often adopt more efficient and cleaner technologies, potentially leading to a decrease in CO<sub>2</sub> emissions, as observed in the research by Zhang and Hanaoka [118] and Balsalobre-Lorente et al. [119]. Urbanization, characterized by the concentration of population and industries, initially contributes to higher emissions through intensified energy use and construction. However, in advanced stages, urbanization can lead to more efficient energy use and reduced CO<sub>2</sub> emissions per capita, a phenomenon explored in the works of Cheng and Hu [120], Tan et al. [121], Han et al. [122], Lee et al. [123], and Xu et al. [124]. Industrialization's impact on CO<sub>2</sub> emissions is initially positive due to its reliance on fossil fuels and high-energy-consuming manufacturing processes, as discussed in the research by Das et al. [125] and Fan et al. [126]. However, as industrial processes become more efficient and shift towards less energy-intensive sectors, this impact can become negative (Voumik et al. [127] and Shang et al. [128]). Trade, often associated with higher emissions due to increased transportation and production, also has the potential to reduce emissions through the diffusion of green technologies and practices, as demonstrated in the studies by Raihan [129], Suhrab et al. [130], and Ntiamoah et al. [131]. These results underscore the complex yet pivotal role of economic development in shaping the environmental sustainability of OECD countries. They align with the OECD's environmental sustainability program, which focuses on sustainable economic growth, efficient resource use, and the integration of environmental considerations into policy-making, emphasizing the transition to greener economies and the adoption of sustainable practices.

#### 4.3. Dumitrescu–Hurlin Panel Causality Test

Because the Machado–Mata quantile regression method has some flaws, like not being able to look at causal relationships between variables, this study uses a different set of methods. To explore the causal linkages between the studied variables, the Dumitrescu–Hurlin panel causality test, as proposed by Dumitrescu and Hurlin [100], is utilized. This

test is particularly suited for panel data and is capable of handling the heterogeneity inherent in such datasets. The Dumitrescu–Hurlin test offers a robust analysis of the direction and nature of causality among multiple variables over time, thereby providing deeper insights into the dynamic interactions within the dataset. The outcomes derived from applying this causality test are presented in Table 4. These results are crucial for understanding not only the relationships among the variables but also the directional influence they exert on each other, thereby significantly contributing to the better analysis of the data under study.

**Table 4.** The results of the Dumitrescu–Hurlin panel causality test.

Hull Hypothesis	Wald Statistics	Z Statistics	p-Value
re $\neq$ co	3.536 ***	4.036	0.000
co $\neq$ re	5.468 ***	5.012	0.000
en $\neq$ co	6.807 ***	5.596	0.000
co $\neq$ en	5.252 ***	4.718	0.000
gr $\neq$ co	2.372 *	1.659	0.074
co $\neq$ gr	7.846 ***	8.617	0.000
tr $\neq$ co	3.128 **	3.383	0.013
co $\neq$ tr	2.286 *	2.005	0.059
ur $\neq$ co	7.323 ***	6.475	0.000
co $\neq$ ur	4.014 ***	3.872	0.000
in $\neq$ co	5.548 ***	4.922	0.000
co $\neq$ in	7.406 ***	8.295	0.000

Note: \*\*\* a 1% significant level; \*\* a 5% significant level; \* a 10% significant level.

The empirical results presented in Table 4 derived from the application of the Dumitrescu–Hurlin panel causality test reveal statistically significant Wald statistics with  $p$ -values below 0.10, 0.05, and 0.001. These  $p$ -values correspond to significance levels of 10%, 5%, and 1%, respectively, leading to the rejection of the null hypothesis of no causality. The findings specifically indicate a bidirectional causal relationship between CO<sub>2</sub> emissions and several key variables: renewable energy consumption, environmental technologies, gross domestic product, trade, urbanization, and industrialization. These bidirectional causalities suggest a complex and interactive relationship between CO<sub>2</sub> emissions and the aforementioned economic and environmental factors. For instance, while renewable energy consumption and the development of environmental technologies can influence the level of CO<sub>2</sub> emissions, changes in emissions can also affect the adoption and effectiveness of these measures. Similarly, the interplay between CO<sub>2</sub> emissions and GDP, trade, urbanization, and industrialization highlights the reciprocal influence of economic growth and environmental impact. Such dynamics align with the findings of research conducted by Huang and Yi [132], Zhang et al. [133], and Song et al. [134], which also observed significant interdependencies between these variables. These interactions underscore the critical need for policy interventions that consider the mutual impact of environmental and economic variables. Policies aimed at reducing CO<sub>2</sub> emissions, for instance, should account for their potential effects on economic factors like GDP and trade, and vice versa. This integrative approach is essential for achieving sustainable development goals and fostering a balanced relationship between economic growth and environmental stewardship.

#### 4.4. Robustness Test

While the Machado–Mata quantile regression method yields significant empirical estimates within this study, it is imperative to corroborate these findings to ensure their robustness and reliability. To achieve this, the study introduces an additional analytical layer by applying standard quantile regression as a robustness check. Quantile regression, distinct from Machado–Mata quantile regression, offers a better understanding of the data distribution, particularly in examining the conditional medians and other quantiles of the dependent variable. This method is particularly effective in capturing the impact of



independent variables across different points in the distribution of the dependent variable, thus providing a comprehensive understanding of the relationships under study. The results of this standard quantile regression analysis are systematically presented in Table 5.

**Table 5.** The results of the robustness test.

Variable and Model	Model (7)	Model (8)	Model (9)	Model (10)
	Q <sub>0.25</sub>	Q <sub>0.50</sub>	Q <sub>0.75</sub>	Q <sub>0.90</sub>
re	−0.202 *** (−6.112)	−0.186 *** (−5.426)	−0.117 *** (−5.549)	−0.104 *** (−5.288)
en	−0.061 *** (−3.539)	−0.057 *** (−3.388)	−0.051 *** (−3.709)	−0.049 *** (−4.077)
gr	0.905 *** (2.617)	0.885 *** (2.834)	0.841 *** (2.916)	0.795 *** (2.638)
tr	−0.301 ** (−2.035)	−0.282 * (−1.825)	−0.205 (−1.243)	−0.124 (−1.478)
ur	−0.469 ** (−2.724)	0.434 * (1.825)	0.405 ** (2.026)	0.398 (1.109)
in	−0.563 * (−1.805)	0.516 *** (2.768)	0.487 ** (2.005)	0.433 (1.534)
c	−2.678 * (−1.825)	−1.865 (−1.203)	−2.533 * (−1.781)	−1.379 (−1.348)

Note: c constant; t-statistical value shown in parentheses; \*\*\* a 1% significant level; \*\* a 5% significant level; \* a 1% significant level.

The outcomes depicted in Table 5, while exhibiting minor variances in the magnitude and statistical significance of the coefficients, largely correspond with those presented in Table 3. This consistency suggests a degree of congruence in the findings obtained from different analytical approaches. Similarly, the results derived from the application of standard quantile regression are found to be consistent with those obtained through the Machado–Mata quantile regression method. This alignment across various methodological frameworks reinforces the credibility and robustness of the study’s findings. Such congruence between different statistical models is indicative of the reliability of the empirical estimates. The slight variations in coefficient sizes and significance levels can be attributed to the inherent methodological nuances of each statistical approach. However, the overarching agreement in the direction and relative impact of the variables under study across these models lends substantial weight to the validity of the conclusions drawn. This cross-methodological validation is crucial in empirical research, as it provides a comprehensive and multi-faceted understanding of the data, thereby enhancing the overall integrity and reliability of the research outcomes.

## 5. Conclusions

The study examines the relationship between economic growth and environmental sustainability in OECD countries from 1990 to 2022, revealing a significant inverse link between renewable energy use and CO<sub>2</sub> emissions. This underscores renewable energy’s vital role in reducing environmental impacts. It also highlights how environmental technologies markedly decrease emissions, emphasizing the importance of innovation in this area. The research details how economic development factors initially contribute to higher emissions, but this trend reverses as economies adopt greener technologies, reflecting a shift towards sustainable practices. The study supports the OECD’s goals of sustainable growth and environmental integration in policymaking, advocating for strategies that balance economic advancement with ecological conservation. This approach, promoting renewable energy and environmental technologies, offers key insights for policymakers, stressing the need for a comprehensive approach to long-term environmental sustainability.

Drawing upon the insights derived from this study, several policy recommendations, coupled with practical solutions, are elucidated. Firstly, the observed negative correlation

between renewable energy consumption and CO<sub>2</sub> emissions mandates the reinforcement of policies that promote renewable energy sources. Governments in OECD countries should prioritize investments in renewable energy infrastructure, including wind, solar, and hydroelectric power. Incentives for businesses and households to adopt renewable energy sources, such as tax credits or subsidies, can accelerate this transition. This policy direction will significantly reduce the environmental impact of energy consumption. Secondly, the study underscores the necessity of fostering technological advancements in environmental conservation. Policy frameworks should be designed to encourage research and development in environmental technologies, particularly those that enhance energy efficiency and reduce emissions. This could involve funding initiatives for green technology research, creating incubators for environmental startups, and providing grants or tax breaks for companies that develop and deploy such technologies. Thirdly, recognizing the dual impact of GDP growth, urbanization, industrialization, and trade on CO<sub>2</sub> emissions, it is imperative to adopt a balanced approach to economic development. Policies should be formulated to ensure that economic expansion is coupled with environmental considerations. This includes integrating sustainable practices into urban planning, promoting eco-friendly industrial processes, and encouraging sustainable trade practices. Finally, given the interconnected nature of global economies, international collaboration is essential to addressing environmental challenges. OECD countries should take the lead in forming global alliances and agreements focused on environmental sustainability. Sharing best practices, technology transfers, and joint initiatives on renewable energy and environmental technologies can have a significant positive impact on global environmental sustainability efforts.

In the course of this research, certain limitations emerged that warrant acknowledgment. Firstly, the study's focus on OECD countries may not fully represent the global dynamics of renewable energy adoption and its impact on CO<sub>2</sub> emissions. Variations in economic development, policy frameworks, and cultural attitudes in non-OECD countries could offer different insights. Future studies could include a more diverse set of countries, encompassing both developed and developing nations outside the OECD. This would provide a more comprehensive understanding of the global environmental sustainability landscape. Secondly, the research primarily considers macroeconomic variables like GDP, urbanization, and trade. It potentially overlooks micro-level factors such as consumer behavior, corporate environmental responsibility, and specific policy measures. Subsequent studies could delve into micro-level factors, such as consumer behavior towards renewable energy, corporate sustainability practices, and the effectiveness of specific environmental policies at a more granular level. Finally, the research does not fully address other potential confounding factors that might influence the relationship between economic development and environmental sustainability, such as political stability, international trade agreements, and global economic shifts. Future research could explore the impact of additional confounding factors like geopolitical events, international environmental agreements, and global economic trends on the relationship between economic development and environmental sustainability.

**Author Contributions:** Conceptualization, Y.H.; methodology, Y.H.; software, X.L.; validation, R.W.; formal analysis, R.W.; investigation, X.L.; resources, R.W.; data curation, X.L.; writing—original draft preparation, X.L.; writing—review and editing, Y.H.; visualization, R.W.; supervision, Y.H. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** The data presented in this study are available from the author upon request.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## References

1. Chu, L.K. Environmentally Related Technologies and Environmental Regulations in Promoting Renewable Energy: Evidence from OECD Countries. *J. Environ. Stud. Sci.* **2023**, *13*, 177–197. [[CrossRef](#)]
2. Saqib, N.; Ozturk, I.; Usman, M. Investigating the Implications of Technological Innovations, Financial Inclusion, and Renewable Energy in Diminishing Ecological Footprints Levels in Emerging Economies. *Geosci. Front.* **2023**, *14*, 101667. [[CrossRef](#)]
3. Dam, M.M.; İşık, C.; Ongan, S. The Impacts of Renewable Energy and Institutional Quality in Environmental Sustainability in the Context of the Sustainable Development Goals: A Novel Approach with the Inverted Load Capacity Factor. *Environ. Sci. Pollut. Res.* **2023**, *30*, 95394–95409. [[CrossRef](#)] [[PubMed](#)]
4. Behera, P.; Haldar, A.; Sethi, N. Achieving Carbon Neutrality Target in the Emerging Economies: Role of Renewable Energy and Green Technology. *Gondwana Res.* **2023**, *121*, 16–32. [[CrossRef](#)]
5. Xu, D.; Abbas, S.; Rafique, K.; Ali, N. The Race to Net-Zero Emissions: Can Green Technological Innovation and Environmental Regulation Be the Potential Pathway to Net-Zero Emissions? *Technol. Soc.* **2023**, *75*, 102364. [[CrossRef](#)]
6. Adebayo, T.S.; Ullah, S. Towards a Sustainable Future: The Role of Energy Efficiency, Renewable Energy, and Urbanization in Limiting CO<sub>2</sub> Emissions in Sweden. *Sustain. Dev.* **2023**, *30*, sd.2658. [[CrossRef](#)]
7. Voumik, L.C.; Ridwan, M.; Rahman, M.H.; Raihan, A. An Investigation into the Primary Causes of Carbon Dioxide Releases in Kenya: Does Renewable Energy Matter to Reduce Carbon Emission? *Renew. Energy Focus* **2023**, *47*, 100491. [[CrossRef](#)]
8. Hasni, R.; Dridi, D.; Ben Jebli, M. Do Financial Development, Financial Stability and Renewable Energy Disturb Carbon Emissions? Evidence from Asia-Pacific Economic Cooperation Economics. *Environ. Sci. Pollut. Res.* **2023**, *30*, 83198–83213. [[CrossRef](#)]
9. Saqib, N.; Dinca, G. Exploring the Asymmetric Impact of Economic Complexity, FDI, and Green Technology on Carbon Emissions: Policy Stringency for Clean-Energy Investing Countries. *Geosci. Front.* **2023**, 101671. [[CrossRef](#)]
10. Alola, A.A.; Adebayo, T.S. Are Green Resource Productivity and Environmental Technologies the Face of Environmental Sustainability in the Nordic Region? *Sustain. Dev.* **2023**, *31*, 760–772. [[CrossRef](#)]
11. Huo, W.; Zaman, B.U.; Zulfiqar, M.; Kocak, E.; Shehzad, K. How Do Environmental Technologies Affect Environmental Degradation? Analyzing the Direct and Indirect Impact of Financial Innovations and Economic Globalization. *Environ. Technol. Innov.* **2023**, *29*, 102973. [[CrossRef](#)]
12. Cicerone, G.; Faggian, A.; Montresor, S.; Rentocchini, F. Regional Artificial Intelligence and the Geography of Environmental Technologies: Does Local AI Knowledge Help Regional Green-Tech Specialization? *Reg. Stud.* **2023**, *57*, 330–343. [[CrossRef](#)]
13. Albitar, K.; Borgi, H.; Khan, M.; Zahra, A. Business Environmental Innovation and CO<sub>2</sub> Emissions: The Moderating Role of Environmental Governance. *Bus. Strat. Environ.* **2023**, *32*, 1996–2007. [[CrossRef](#)]
14. Huang, J.; Yan, Y.; Kang, J.; Peng, W.; Wang, A. Driving Technology Factors of Carbon Emissions: Theoretical Framework and Its Policy Implications for China. *Sci. Total Environ.* **2023**, *904*, 166858. [[CrossRef](#)] [[PubMed](#)]
15. Omri, E.; Saadaoui, H. An Empirical Investigation of the Relationships between Nuclear Energy, Economic Growth, Trade Openness, Fossil Fuels, and Carbon Emissions in France: Fresh Evidence Using Asymmetric Cointegration. *Environ. Sci. Pollut. Res.* **2022**, *30*, 13224–13245. [[CrossRef](#)]
16. Karakurt, I.; Aydin, G. Development of Regression Models to Forecast the CO<sub>2</sub> Emissions from Fossil Fuels in the BRICS and MINT Countries. *Energy* **2023**, *263*, 125650. [[CrossRef](#)]
17. Gielen, D.; Boshell, F.; Saygin, D.; Bazilian, M.D.; Wagner, N.; Gorini, R. The Role of Renewable Energy in the Global Energy Transformation. *Energy Strategy Rev.* **2019**, *24*, 38–50. [[CrossRef](#)]
18. Berdysheva, S.; Ikonnikova, S. The Energy Transition and Shifts in Fossil Fuel Use: The Study of International Energy Trade and Energy Security Dynamics. *Energies* **2021**, *14*, 5396. [[CrossRef](#)]
19. Bell, S. The Renewable Energy Transition Energy Path Divergence, Increasing Returns and Mutually Reinforcing Leads in the State-Market Symbiosis. *New Political Econ.* **2020**, *25*, 57–71. [[CrossRef](#)]
20. Neagu, O. The Link between Economic Complexity and Carbon Emissions in the European Union Countries: A Model Based on the Environmental Kuznets Curve (EKC) Approach. *Sustainability* **2019**, *11*, 4753. [[CrossRef](#)]
21. Yao, S.; Zhang, S.; Zhang, X. Renewable Energy, Carbon Emission and Economic Growth: A Revised Environmental Kuznets Curve Perspective. *J. Clean. Prod.* **2019**, *235*, 1338–1352. [[CrossRef](#)]
22. Arnaut, J.; Lidman, J. Environmental Sustainability and Economic Growth in Greenland: Testing the Environmental Kuznets Curve. *Sustainability* **2021**, *13*, 1228. [[CrossRef](#)]
23. Wei, C.; Li, C.-Z.; Löschel, A.; Managi, S.; Lundgren, T. Digital Technology and Energy Sustainability: Recent Advances, Challenges, and Opportunities. *Resour. Conserv. Recycl.* **2023**, *190*, 106803. [[CrossRef](#)]
24. Liu, M.; Chen, Z.; Sowah, J.K., Jr.; Ahmed, Z.; Kirikkaleli, D. The Dynamic Impact of Energy Productivity and Economic Growth on Environmental Sustainability in South European Countries. *Gondwana Res.* **2023**, *115*, 116–127. [[CrossRef](#)]
25. Ahakwa, I.; Xu, Y.; Tackie, E.A.; Odai, L.A.; Sarpong, F.A.; Korankye, B.; Ofori, E.K. Do Natural Resources and Green Technological Innovation Matter in Addressing Environmental Degradation? Evidence from Panel Models Robust to Cross-Sectional Dependence and Slope Heterogeneity. *Resour. Policy* **2023**, *85*, 103943. [[CrossRef](#)]
26. Mikulčić, H.; Baleta, J.; Klemeš, J.J.; Wang, X. Energy Transition and the Role of System Integration of the Energy, Water and Environmental Systems. *J. Clean. Prod.* **2021**, *292*, 126027. [[CrossRef](#)]

27. Gupta, A.; Paul, A.R.; Saha, S.C. Decarbonizing the Atmosphere Using Carbon Capture, Utilization, and Sequestration: Challenges, Opportunities, and Policy Implications in India. *Atmosphere* **2023**, *14*, 1546. [[CrossRef](#)]
28. Ren, S.; Hao, Y.; Wu, H. Digitalization and Environment Governance: Does Internet Development Reduce Environmental Pollution? *J. Environ. Plan. Manag.* **2023**, *66*, 1533–1562. [[CrossRef](#)]
29. Zhang, M.; Liu, Y. Influence of Digital Finance and Green Technology Innovation on China's Carbon Emission Efficiency: Empirical Analysis Based on Spatial Metrology. *Sci. Total Environ.* **2022**, *838*, 156463. [[CrossRef](#)] [[PubMed](#)]
30. Dell'Anna, F. Green Jobs and Energy Efficiency as Strategies for Economic Growth and the Reduction of Environmental Impacts. *Energy Policy* **2021**, *149*, 112031. [[CrossRef](#)]
31. Awasthi, M.K.; Sarsaiya, S.; Patel, A.; Juneja, A.; Singh, R.P.; Yan, B.; Awasthi, S.K.; Jain, A.; Liu, T.; Duan, Y. Refining Biomass Residues for Sustainable Energy and Bio-Products: An Assessment of Technology, Its Importance, and Strategic Applications in Circular Bio-Economy. *Renew. Sustain. Energy Rev.* **2020**, *127*, 109876.
32. Capodaglio, A.G.; Olsson, G. Energy Issues in Sustainable Urban Wastewater Management: Use, Demand Reduction and Recovery in the Urban Water Cycle. *Sustainability* **2019**, *12*, 266. [[CrossRef](#)]
33. Li, Y.; Dai, J.; Cui, L. The Impact of Digital Technologies on Economic and Environmental Performance in the Context of Industry 4.0: A Moderated Mediation Model. *Int. J. Prod. Econ.* **2020**, *229*, 107777. [[CrossRef](#)]
34. Yang, X.; Jia, Z.; Yang, Z.; Yuan, X. The Effects of Technological Factors on Carbon Emissions from Various Sectors in China—A Spatial Perspective. *J. Clean. Prod.* **2021**, *301*, 126949. [[CrossRef](#)]
35. Vinuesa, R.; Azizpour, H.; Leite, I.; Balaam, M.; Dignum, V.; Domisch, S.; Felländer, A.; Langhans, S.D.; Tegmark, M.; Fuso Nerini, F. The Role of Artificial Intelligence in Achieving the Sustainable Development Goals. *Nat. Commun.* **2020**, *11*, 233. [[CrossRef](#)] [[PubMed](#)]
36. Nishant, R.; Kennedy, M.; Corbett, J. Artificial Intelligence for Sustainability: Challenges, Opportunities, and a Research Agenda. *Int. J. Inf. Manag.* **2020**, *53*, 102104. [[CrossRef](#)]
37. Galaz, V.; Centeno, M.A.; Callahan, P.W.; Causevic, A.; Patterson, T.; Brass, I.; Baum, S.; Farber, D.; Fischer, J.; Garcia, D. Artificial Intelligence, Systemic Risks, and Sustainability. *Technol. Soc.* **2021**, *67*, 101741. [[CrossRef](#)]
38. Ang, Y.Q.; Berzolla, Z.M.; Letellier-Duchesne, S.; Jusiega, V.; Reinhart, C. UBE.M. Io: A Web-Based Framework to Rapidly Generate Urban Building Energy Models for Carbon Reduction Technology Pathways. *Sustain. Cities Soc.* **2022**, *77*, 103534. [[CrossRef](#)]
39. Newton, P.W.; Rogers, B.C. Transforming Built Environments: Towards Carbon Neutral and Blue-Green Cities. *Sustainability* **2020**, *12*, 4745. [[CrossRef](#)]
40. Chen, J.; Lu, L.; Gong, Q. Techno-Economic and Environmental Evaluation on Radiative Sky Cooling-Based Novel Passive Envelope Strategies to Achieve Building Sustainability and Carbon Neutrality. *Appl. Energy* **2023**, *349*, 121679. [[CrossRef](#)]
41. Dong, F.; Hu, M.; Gao, Y.; Liu, Y.; Zhu, J.; Pan, Y. How Does Digital Economy Affect Carbon Emissions? Evidence from Global 60 Countries. *Sci. Total Environ.* **2022**, *852*, 158401. [[CrossRef](#)] [[PubMed](#)]
42. Ma, Q.; Tariq, M.; Mahmood, H.; Khan, Z. The Nexus between Digital Economy and Carbon Dioxide Emissions in China: The Moderating Role of Investments in Research and Development. *Technol. Soc.* **2022**, *68*, 101910. [[CrossRef](#)]
43. Yi, M.; Liu, Y.; Sheng, M.S.; Wen, L. Effects of Digital Economy on Carbon Emission Reduction: New Evidence from China. *Energy Policy* **2022**, *171*, 113271. [[CrossRef](#)]
44. Dorst, H.; Van der Jagt, A.; Raven, R.; Runhaar, H. Urban Greening through Nature-Based Solutions—Key Characteristics of an Emerging Concept. *Sustain. Cities Soc.* **2019**, *49*, 101620. [[CrossRef](#)]
45. Fan, F.; Lian, H.; Liu, X.; Wang, X. Can Environmental Regulation Promote Urban Green Innovation Efficiency? An Empirical Study Based on Chinese Cities. *J. Clean. Prod.* **2021**, *287*, 125060. [[CrossRef](#)]
46. Feng, Y.; Wang, X.; Liang, Z. How Does Environmental Information Disclosure Affect Economic Development and Haze Pollution in Chinese Cities? The Mediating Role of Green Technology Innovation. *Sci. Total Environ.* **2021**, *775*, 145811. [[CrossRef](#)] [[PubMed](#)]
47. Stern, N.; Valero, A. Innovation, Growth and the Transition to Net-Zero Emissions. *Res. Policy* **2021**, *50*, 104293. [[CrossRef](#)]
48. Bataille, C.G.F. Physical and Policy Pathways to Net-zero Emissions Industry. *WIREs Clim. Chang.* **2020**, *11*, e633. [[CrossRef](#)]
49. Chou, J.; Li, Y.; Xu, Y.; Zhao, W.; Li, J.; Hao, Y. Carbon Dioxide Emission Characteristics and Peak Trend Analysis of Countries along the Belt and Road. *Environ. Sci. Pollut. Res.* **2022**, *30*, 81881–81895. [[CrossRef](#)]
50. Favero, A.; Baker, J.; Sohngen, B.; Daigneault, A. Economic Factors Influence Net Carbon Emissions of Forest Bioenergy Expansion. *Commun. Earth Environ.* **2023**, *4*, 41. [[CrossRef](#)]
51. Sadiq, M.; Shinwari, R.; Usman, M.; Ozturk, I.; Maghyreh, A.I. Linking Nuclear Energy, Human Development and Carbon Emission in BRICS Region: Do External Debt and Financial Globalization Protect the Environment? *Nucl. Eng. Technol.* **2022**, *54*, 3299–3309. [[CrossRef](#)]
52. Anwar, A.; Younis, M.; Ullah, I. Impact of Urbanization and Economic Growth on CO<sub>2</sub> Emission: A Case of Far East Asian Countries. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2531. [[CrossRef](#)]
53. Pu, Y.; Wang, Y.; Wang, P. Driving Effects of Urbanization on City-Level Carbon Dioxide Emissions: From Multiple Perspectives of Urbanization. *Int. J. Urban Sci.* **2022**, *26*, 108–128. [[CrossRef](#)]
54. Zhang, T.; Song, Y.; Yang, J. Relationships between Urbanization and CO<sub>2</sub> Emissions in China: An Empirical Analysis of Population Migration. *PLoS ONE* **2021**, *16*, e0256335. [[CrossRef](#)]



55. Mardani, A.; Liao, H.; Nilashi, M.; Alrasheedi, M.; Cavallaro, F. A Multi-Stage Method to Predict Carbon Dioxide Emissions Using Dimensionality Reduction, Clustering, and Machine Learning Techniques. *J. Clean. Prod.* **2020**, *275*, 122942. [[CrossRef](#)]
56. Magazzino, C.; Mele, M.; Schneider, N. A Machine Learning Approach on the Relationship among Solar and Wind Energy Production, Coal Consumption, GDP, and CO<sub>2</sub> Emissions. *Renew. Energy* **2021**, *167*, 99–115. [[CrossRef](#)]
57. Farahzadi, L.; Kioumars, M. Application of Machine Learning Initiatives and Intelligent Perspectives for CO<sub>2</sub> Emissions Reduction in Construction. *J. Clean. Prod.* **2023**, *384*, 135504. [[CrossRef](#)]
58. Magazzino, C.; Mele, M. A New Machine Learning Algorithm to Explore the CO<sub>2</sub> Emissions-Energy Use-Economic Growth Trilemma. *Ann. Oper. Res.* **2022**, *1*, 1–19. [[CrossRef](#)]
59. Chen, Q.; Taylor, D. Economic Development and Pollution Emissions in Singapore: Evidence in Support of the Environmental Kuznets Curve Hypothesis and Its Implications for Regional Sustainability. *J. Clean. Prod.* **2020**, *243*, 118637. [[CrossRef](#)]
60. Cansino, J.M.; Román-Collado, R.; Molina, J.C. Quality of Institutions, Technological Progress, and Pollution Havens in Latin America. An Analysis of the Environmental Kuznets Curve Hypothesis. *Sustainability* **2019**, *11*, 3708. [[CrossRef](#)]
61. Zhang, Z.; Bashir, T.; Song, J.; Aziz, S.; Yahya, G.; Bashir, S.; Zamir, A. The Effects of Environmental Kuznets Curve toward Environmental Pollution, Energy Consumption on Sustainable Economic Growth through Moderate Role of Technological Innovation. *Environ. Sci. Pollut. Res.* **2022**, *29*, 405–416. [[CrossRef](#)]
62. Wang, S.; Li, C.; Zhou, H. Impact of China's Economic Growth and Energy Consumption Structure on Atmospheric Pollutants: Based on a Panel Threshold Model. *J. Clean. Prod.* **2019**, *236*, 117694. [[CrossRef](#)]
63. Wu, H.; Xu, L.; Ren, S.; Hao, Y.; Yan, G. How Do Energy Consumption and Environmental Regulation Affect Carbon Emissions in China? New Evidence from a Dynamic Threshold Panel Model. *Resour. Policy* **2020**, *67*, 101678. [[CrossRef](#)]
64. Ahmed, Z.; Ahmad, M.; Murshed, M.; Shah, M.I.; Mahmood, H.; Abbas, S. How Do Green Energy Technology Investments, Technological Innovation, and Trade Globalization Enhance Green Energy Supply and Stimulate Environmental Sustainability in the G7 Countries? *Gondwana Res.* **2022**, *112*, 105–115. [[CrossRef](#)]
65. Sharif, A.; Kocak, S.; Khan, H.H.A.; Uzuner, G.; Tiwari, S. Demystifying the Links between Green Technology Innovation, Economic Growth, and Environmental Tax in ASEAN-6 Countries: The Dynamic Role of Green Energy and Green Investment. *Gondwana Res.* **2023**, *115*, 98–106. [[CrossRef](#)]
66. Paramati, S.R.; Shahzad, U.; Doğan, B. The Role of Environmental Technology for Energy Demand and Energy Efficiency: Evidence from OECD Countries. *Renew. Sustain. Energy Rev.* **2022**, *153*, 111735. [[CrossRef](#)]
67. Mensah, C.N.; Long, X.; Dauda, L.; Boamah, K.B.; Salman, M.; Appiah-Twum, F.; Tachie, A.K. Technological Innovation and Green Growth in the Organization for Economic Cooperation and Development Economies. *J. Clean. Prod.* **2019**, *240*, 118204. [[CrossRef](#)]
68. Chakraborty, S.K.; Mazzanti, M. Energy Intensity and Green Energy Innovation: Checking Heterogeneous Country Effects in the OECD. *Struct. Chang. Econ. Dyn.* **2020**, *52*, 328–343. [[CrossRef](#)]
69. Gozgor, G.; Mahalik, M.K.; Demir, E.; Padhan, H. The Impact of Economic Globalization on Renewable Energy in the OECD Countries. *Energy Policy* **2020**, *139*, 111365. [[CrossRef](#)]
70. Samant, S.; Thakur-Wernz, P.; Hatfield, D.E. Does the Focus of Renewable Energy Policy Impact the Nature of Innovation? Evidence from Emerging Economies. *Energy Policy* **2020**, *137*, 111119. [[CrossRef](#)]
71. Zhao, J.; Sinha, A.; Inuwa, N.; Wang, Y.; Murshed, M.; Abbasi, K.R. Does Structural Transformation in Economy Impact Inequality in Renewable Energy Productivity? Implications for Sustainable Development. *Renew. Energy* **2022**, *189*, 853–864. [[CrossRef](#)]
72. Saqib, N.; Usman, M.; Mahmood, H.; Abbas, S.; Ahmad, F.; Mihai, D.; Mallek, R.S. The Moderating Role of Technological Innovation and Renewable Energy on CO<sub>2</sub> Emission in O.E.C.D. Countries: Evidence from Panel Quantile Regression Approach. *Econ. Res.* **2023**, *36*, 2168720. [[CrossRef](#)]
73. Bashir, M.A.; Dengfeng, Z.; Bashir, M.F.; Rahim, S.; Xi, Z. Exploring the Role of Economic and Institutional Indicators for Carbon and GHG Emissions: Policy-Based Analysis for OECD Countries. *Environ. Sci. Pollut. Res.* **2022**, *30*, 32722–32736. [[CrossRef](#)]
74. Ulucak, R.; Danish; Kassouri, Y. An Assessment of the Environmental Sustainability Corridor: Investigating the Non-linear Effects of Environmental Taxation on CO<sub>2</sub> Emissions. *Sustain. Dev.* **2020**, *28*, 1010–1018. [[CrossRef](#)]
75. Mardani, A.; Streimikiene, D.; Cavallaro, F.; Loganathan, N.; Khoshnoudi, M. Carbon Dioxide (CO<sub>2</sub>) Emissions and Economic Growth: A Systematic Review of Two Decades of Research from 1995 to 2017. *Sci. Total Environ.* **2019**, *649*, 31–49. [[CrossRef](#)]
76. Iram, R.; Zhang, J.; Erdogan, S.; Abbas, Q.; Mohsin, M. Economics of Energy and Environmental Efficiency: Evidence from OECD Countries. *Environ. Sci. Pollut. Res.* **2020**, *27*, 3858–3870. [[CrossRef](#)]
77. Mirziyoyeva, Z.; Salahodjaev, R. Renewable Energy, GDP and CO<sub>2</sub> Emissions in High-Globalized Countries. *Front. Energy Res.* **2023**, *11*, 1123269. [[CrossRef](#)]
78. Tariq, G.; Sun, H.; Ali, I.; Pasha, A.A.; Khan, M.S.; Rahman, M.M.; Mohamed, A.; Shah, Q. Influence of Green Technology, Green Energy Consumption, Energy Efficiency, Trade, Economic Development and FDI on Climate Change in South Asia. *Sci. Rep.* **2022**, *12*, 16376. [[PubMed](#)]
79. Lasisi, T.T.; Alola, A.A.; Muoneke, O.B.; Eluwole, K.K. The Moderating Role of Environmental-Related Innovation and Technologies in Growth-Energy Utilization Nexus in Highest-Performing Eco-Innovation Economies. *Technol. Forecast. Soc. Chang.* **2022**, *183*, 121953. [[CrossRef](#)]



80. Razaq, A.; Sharif, A.; Afshan, S.; Li, C.J. Do Climate Technologies and Recycling Asymmetrically Mitigate Consumption-Based Carbon Emissions in the United States? New Insights from Quantile ARDL. *Technol. Forecast. Soc. Chang.* **2023**, *186*, 122138. [[CrossRef](#)]
81. He, Y.; Li, X.; Huang, P.; Wang, J. Exploring the Road toward Environmental Sustainability: Natural Resources, Renewable Energy Consumption, Economic Growth, and Greenhouse Gas Emissions. *Sustainability* **2022**, *14*, 1579. [[CrossRef](#)]
82. He, Y. Unraveling the Interplay between Food Security, Agriculture, Trade Policy, and Energy Consumption: An Environmental Sustainability Insight. *Energy Environ.* **2023**, 0958305X231195604. [[CrossRef](#)]
83. Kang, H. CO<sub>2</sub> Emissions Embodied in International Trade and Economic Growth: Empirical Evidence for OECD and Non-OECD Countries. *Sustainability* **2021**, *13*, 12114. [[CrossRef](#)]
84. Wang, W.-Z.; Liu, L.-C.; Liao, H.; Wei, Y.-M. Impacts of Urbanization on Carbon Emissions: An Empirical Analysis from OECD Countries. *Energy Policy* **2021**, *151*, 112171. [[CrossRef](#)]
85. He, Y. Investigating the Routes toward Environmental Sustainability: Fresh Insights from Korea. *Sustainability* **2023**, *15*, 602. [[CrossRef](#)]
86. Wu, R.; Xie, Z. Identifying the Impacts of Income Inequality on CO<sub>2</sub> Emissions: Empirical Evidences from OECD Countries and Non-OECD Countries. *J. Clean. Prod.* **2020**, *277*, 123858. [[CrossRef](#)]
87. Wang, Y.; He, Y. Does Information and Communication Technology Trade Openness Matter for China's Energy Transformation and Environmental Quality? *Energies* **2023**, *16*, 2016. [[CrossRef](#)]
88. York, R.; Rosa, E.A.; Dietz, T. STIRPAT, IPAT and ImPACT: Analytic Tools for Unpacking the Driving Forces of Environmental Impacts. *Ecol. Econ.* **2003**, *46*, 351–365. [[CrossRef](#)]
89. Van Le, C.; Luong, T.A.; Nguyen, M.-H.; Hoang, V.-N. The Relative Roles of Domestic and Foreign Capital in Aggregate Production of GDP and CO<sub>2</sub>-Equivalent Emission across OECD Countries. *Environ. Sci. Pollut. Res.* **2022**, *30*, 32052–32064. [[CrossRef](#)] [[PubMed](#)]
90. He, Y. Renewable and Non-Renewable Energy Consumption and Trade Policy: Do They Matter for Environmental Sustainability? *Energies* **2022**, *15*, 3559. [[CrossRef](#)]
91. Liao, J.; Liu, X.; Zhou, X.; Tursunova, N.R. Analyzing the Role of Renewable Energy Transition and Industrialization on Ecological Sustainability: Can Green Innovation Matter in OECD Countries. *Renew. Energy* **2023**, *204*, 141–151. [[CrossRef](#)]
92. Lee, C.-C.; Zhao, Y.-N. Heterogeneity Analysis of Factors Influencing CO<sub>2</sub> Emissions: The Role of Human Capital, Urbanization, and FDI. *Renew. Sustain. Energy Rev.* **2023**, *185*, 113644. [[CrossRef](#)]
93. Jarque, C.M.; Bera, A.K. A Test for Normality of Observations and Regression Residuals. *Int. Stat. Rev./Rev. Int. Stat.* **1987**, *55*, 163–172. [[CrossRef](#)]
94. Pesaran, M.H.; Yamagata, T. Testing Slope Homogeneity in Large Panels. *J. Econom.* **2008**, *142*, 50–93. [[CrossRef](#)]
95. Pesaran, M.H. General Diagnostic Tests for Cross Section Dependence in Panels. *J. Econom.* **2004**, *69*. [[CrossRef](#)]
96. Pesaran, M.H. A Simple Panel Unit Root Test in the Presence of Cross-section Dependence. *J. Appl. Econom.* **2007**, *22*, 265–312. [[CrossRef](#)]
97. Westerlund, J. Error Correction Based Panel Cointegration Tests. *Oxford Bull. Econ. Stat.* **2007**, *69*, 709–748. [[CrossRef](#)]
98. Koenker, R.; Bassett, G., Jr. Regression Quantiles. *Econom. J. Econom. Soc.* **1978**, *46*, 33–50. [[CrossRef](#)]
99. Machado, J.A.; Silva, J.S. Quantiles via Moments. *J. Econom.* **2019**, *213*, 145–173. [[CrossRef](#)]
100. Dumitrescu, E.-I.; Hurlin, C. Testing for Granger Non-Causality in Heterogeneous Panels. *Econ. Model.* **2012**, *29*, 1450–1460. [[CrossRef](#)]
101. Breitung, J. A Parametric Approach to the Estimation of Cointegration Vectors in Panel Data. *Econom. Rev.* **2005**, *24*, 151–173. [[CrossRef](#)]
102. Yang, M.; Fu, M.; Zhang, Z. The Adoption of Digital Technologies in Supply Chains: Drivers, Process and Impact. *Technol. Forecast. Soc. Chang.* **2021**, *169*, 120795. [[CrossRef](#)]
103. Ma, C.-Q.; Liu, J.-L.; Ren, Y.-S.; Jiang, Y. The Impact of Economic Growth, FDI and Energy Intensity on China's Manufacturing Industry's CO<sub>2</sub> Emissions: An Empirical Study Based on the Fixed-Effect Panel Quantile Regression Model. *Energies* **2019**, *12*, 4800. [[CrossRef](#)]
104. Pata, U.K. Linking Renewable Energy, Globalization, Agriculture, CO<sub>2</sub> Emissions and Ecological Footprint in BRIC Countries: A Sustainability Perspective. *Renew. Energy* **2021**, *173*, 197–208. [[CrossRef](#)]
105. Cui, L.; Weng, S.; Nadeem, A.M.; Rafique, M.Z.; Shahzad, U. Exploring the Role of Renewable Energy, Urbanization and Structural Change for Environmental Sustainability: Comparative Analysis for Practical Implications. *Renew. Energy* **2022**, *184*, 215–224. [[CrossRef](#)]
106. Caglar, A.E.; Mert, M.; Boluk, G. Testing the Role of Information and Communication Technologies and Renewable Energy Consumption in Ecological Footprint Quality: Evidence from World Top 10 Pollutant Footprint Countries. *J. Clean. Prod.* **2021**, *298*, 126784. [[CrossRef](#)]
107. Xue, L.; Haseeb, M.; Mahmood, H.; Alkhateeb, T.T.Y.; Murshed, M. Renewable Energy Use and Ecological Footprints Mitigation: Evidence from Selected South Asian Economies. *Sustainability* **2021**, *13*, 1613. [[CrossRef](#)]
108. Chen, X.H.; Tee, K.; Elnahass, M.; Ahmed, R. Assessing the Environmental Impacts of Renewable Energy Sources: A Case Study on Air Pollution and Carbon Emissions in China. *J. Environ. Manag.* **2023**, *345*, 118525. [[CrossRef](#)] [[PubMed](#)]

109. Christoforidis, T.; Katrakilidis, C. The Dynamic Role of Institutional Quality, Renewable and Non-Renewable Energy on the Ecological Footprint of OECD Countries: Do Institutions and Renewables Function as Leverage Points for Environmental Sustainability? *Environ. Sci. Pollut. Res.* **2021**, *28*, 53888–53907. [[CrossRef](#)]
110. Khan, Y.; Hassan, T.; Tufail, M.; Marie, M.; Imran, M.; Xiuqin, Z. The Nexus between CO<sub>2</sub> Emissions, Human Capital, Technology Transfer, and Renewable Energy: Evidence from Belt and Road Countries. *Environ. Sci. Pollut. Res.* **2022**, *29*, 59816–59834. [[CrossRef](#)] [[PubMed](#)]
111. Fujii, H.; Managi, S. Decomposition Analysis of Sustainable Green Technology Inventions in China. *Technol. Forecast. Soc. Chang.* **2019**, *139*, 10–16. [[CrossRef](#)]
112. Karmaker, S.C.; Hosan, S.; Chapman, A.J.; Saha, B.B. The Role of Environmental Taxes on Technological Innovation. *Energy* **2021**, *232*, 121052. [[CrossRef](#)]
113. Xu, L.; Fan, M.; Yang, L.; Shao, S. Heterogeneous Green Innovations and Carbon Emission Performance: Evidence at China's City Level. *Energy Econ.* **2021**, *99*, 105269. [[CrossRef](#)]
114. Cai, A.; Zheng, S.; Cai, L.; Yang, H.; Comite, U. How Does Green Technology Innovation Affect Carbon Emissions? A Spatial Econometric Analysis of China's Provincial Panel Data. *Front. Environ. Sci.* **2021**, *9*, 813811. [[CrossRef](#)]
115. Zafar, M.W.; Saleem, M.M.; Destek, M.A.; Caglar, A.E. The Dynamic Linkage between Remittances, Export Diversification, Education, Renewable Energy Consumption, Economic Growth, and CO<sub>2</sub> Emissions in Top Remittance-receiving Countries. *Sustain. Dev.* **2022**, *30*, 165–175. [[CrossRef](#)]
116. Odugbesan, J.A.; Rjoub, H. Relationship Among Economic Growth, Energy Consumption, CO<sub>2</sub> Emission, and Urbanization: Evidence from MINT Countries. *SAGE Open* **2020**, *10*, 215824402091464. [[CrossRef](#)]
117. Anser, M.K.; Usman, M.; Godil, D.I.; Shabbir, M.S.; Sharif, A.; Tabash, M.I.; Lopez, L.B. Does Globalization Affect the Green Economy and Environment? The Relationship between Energy Consumption, Carbon Dioxide Emissions, and Economic Growth. *Environ. Sci. Pollut. Res.* **2021**, *28*, 51105–51118. [[CrossRef](#)]
118. Zhang, R.; Hanaoka, T. Deployment of Electric Vehicles in China to Meet the Carbon Neutral Target by 2060: Provincial Disparities in Energy Systems, CO<sub>2</sub> Emissions, and Cost Effectiveness. *Resour. Conserv. Recycl.* **2021**, *170*, 105622. [[CrossRef](#)]
119. Balsalobre-Lorente, D.; Driha, O.M.; Halkos, G.; Mishra, S. Influence of Growth and Urbanization on CO<sub>2</sub> Emissions: The Moderating Effect of Foreign Direct Investment on Energy Use in BRICS. *Sustain. Dev.* **2022**, *30*, 227–240. [[CrossRef](#)]
120. Cheng, Z.; Hu, X. The Effects of Urbanization and Urban Sprawl on CO<sub>2</sub> Emissions in China. *Environ. Dev. Sustain.* **2023**, *25*, 1792–1808. [[CrossRef](#)]
121. Tan, F.; Yang, S.; Niu, Z. The Impact of Urbanization on Carbon Emissions: Both from Heterogeneity and Mechanism Test. *Environ. Dev. Sustain.* **2023**, *25*, 4813–4829. [[CrossRef](#)]
122. Han, X.; He, X.; Xiong, W.; Shi, W. Effects of Urbanization on CO<sub>2</sub> Emissions, Water Use and the Carbon-Water Coupling in a Typical Dual-Core Urban Agglomeration in China. *Urban. Clim.* **2023**, *49*, 101572. [[CrossRef](#)]
123. Lee, C.-C.; Zhou, B.; Yang, T.-Y.; Yu, C.-H.; Zhao, J. The Impact of Urbanization on CO<sub>2</sub> Emissions in China: The Key Role of Foreign Direct Investment. *Emerg. Mark. Financ. Trade* **2023**, *59*, 451–462. [[CrossRef](#)]
124. Xu, J.; Wang, J.; Li, R.; Yang, X. Spatio-Temporal Effects of Urbanization on CO<sub>2</sub> Emissions: Evidences from 268 Chinese Cities. *Energy Policy* **2023**, *177*, 113569. [[CrossRef](#)]
125. Das, N.; Gangopadhyay, P.; Bera, P.; Hossain, M.E. Investigating the Nexus between Carbonization and Industrialization under Kaya's Identity: Findings from Novel Multivariate Quantile on Quantile Regression Approach. *Environ. Sci. Pollut. Res.* **2023**, *30*, 45796–45814. [[CrossRef](#)]
126. Fan, J.; Wang, J.; Qiu, J.; Li, N. Stage Effects of Energy Consumption and Carbon Emissions in the Process of Urbanization: Evidence from 30 Provinces in China. *Energy* **2023**, *276*, 127655. [[CrossRef](#)]
127. Voumik, L.C.; Mimi, M.B.; Raihan, A. Nexus Between Urbanization, Industrialization, Natural Resources Rent, and Anthropogenic Carbon Emissions in South Asia: CS-ARDL Approach. *Anthr. Sci.* **2023**, *2*, 48–61. [[CrossRef](#)]
128. Shang, M.; Ma, Z.; Su, Y.; Shaheen, F.; Khan, R.; Mohd Tahir, L.; Khalid Anser, M.; Zaman, K. Understanding the Importance of Sustainable Ecological Innovation in Reducing Carbon Emissions: Investigating the Green Energy Demand, Financial Development, Natural Resource Management, Industrialisation and Urbanisation Channels. *Econ. Res.* **2023**, *36*, 137823. [[CrossRef](#)]
129. Raihan, A. The Dynamic Nexus between Economic Growth, Renewable Energy Use, Urbanization, Industrialization, Tourism, Agricultural Productivity, Forest Area, and Carbon Dioxide Emissions in the Philippines. *Energy Nexus* **2023**, *9*, 100180. [[CrossRef](#)]
130. Suhrab, M.; Soomro, J.A.; Ullah, S.; Chavara, J. The Effect of Gross Domestic Product, Urbanization, Trade Openness, Financial Development, and Renewable Energy on CO<sub>2</sub> Emission. *Environ. Sci. Pollut. Res.* **2022**, *30*, 22985–22991. [[CrossRef](#)]
131. Ntiamoah, E.B.; Chandio, A.A.; Yeboah, E.N.; Twumasi, M.A.; Siaw, A.; Li, D. How Do Carbon Emissions, Economic Growth, Population Growth, Trade Openness and Employment Influence Food Security? Recent Evidence from the East Africa. *Environ. Sci. Pollut. Res.* **2023**, *30*, 51844–51860. [[CrossRef](#)] [[PubMed](#)]
132. Huang, H.; Yi, M. Impacts and Mechanisms of Heterogeneous Environmental Regulations on Carbon Emissions: An Empirical Research Based on DID Method. *Environ. Impact Assess. Rev.* **2023**, *99*, 107039. [[CrossRef](#)]

133. Zhang, T.; Yin, J.; Li, Z.; Jin, Y.; Ali, A.; Jiang, B. A Dynamic Relationship between Renewable Energy Consumption, Non-Renewable Energy Consumption, Economic Growth and CO<sub>2</sub> Emissions: Evidence from Asian Emerging Economies. *Front. Environ. Sci.* **2023**, *10*, 2721. [[CrossRef](#)]
134. Song, M.-J.; Seo, Y.-J.; Lee, H.-Y. The Dynamic Relationship between Industrialization, Urbanization, CO<sub>2</sub> Emissions, and Transportation Modes in Korea: Empirical Evidence from Maritime and Air Transport. *Transportation* **2023**, *50*, 2111–2137. [[CrossRef](#)]

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.