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Assessing the Damage to Environmental Pollution: Discerning the Impact of Environmental Technology, Energy Efficiency, Green Energy and Natural Resources

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Abstract: The existing literature covers the topic of environmental pollution, but there is a scarcity of research that specifically examines the factors contributing to financial losses caused by carbon emissions. In this perspective, this ongoing analysis provides an understanding of the impact of environmental technology, energy efficiency, renewable energy consumption, natural resources, and economic growth on carbon dioxide damage in Organization for Economic Cooperation and Development (OECD) countries from 2000 to 2021 using the “Method of Moments Quantile Regression (MMQR)”, and “Dumitrescu–Hurlin (D-H)” causality test. The findings from the MMQR revealed that environmental control technology, renewable energy consumption, and energy efficiency contribute to reducing carbon dioxide damage at different quantiles. It was also found that economic growth and natural resources contribute to the increase in carbon dioxide damage in various quantities. Additionally, a one-way causality result was obtained from environmental technology, energy efficiency, renewable energy consumption, natural resources, and economic growth towards carbon dioxide damage. These results indicate that policymakers in OECD nations should provide suggestions on the efficient utilization of renewable energy sources and environmentally friendly technologies to minimize carbon dioxide damage.

Keywords: environmental damage; environmental technology; energy efficiency; green energy; natural resources



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1. Introduction

Environmental pollution has become a global pressing issue [1], causing extreme weather and severe drought [2], rising sea levels [3], food crises, animal extinction [4], biodiversity loss [5], high mortality rate and migration [6], and frequent economic losses [7]. While environmental pollution is a comprehensive term, it is essential to comprehend the impact of greenhouse gas (GHG) emissions, particularly carbon dioxide, on the environment. Human activities leading to anthropogenic GHG emissions are accountable for nearly 95% of global warming [8]. Researchers have estimated that, to meet the ambitious goals of the “Paris Climate Agreement” of keeping the temperature ‘well below’ 2 °C, fossil fuels must be cut by 40% every year until 2030, and the share of renewables must be increased to 60% of the total energy supply, requiring a large scale of investment in

renewable energy enterprises, equaling approximately \$1.8 trillion [9]. However, with energy-dependent global economies, restricting fossil fuel consumption without causing an economic slowdown has become a serious challenge [7]. The importance of striking a balance between economic development and environmental preservation has grown on policymakers' agendas. Therefore, evaluating the economic damage for environmental pollution can serve as an important decision-making reference and provide significant value to the body of environmental economic literature.

Empirically, scholars have holistically examined many determinants of ecological pollution, e.g., economic growth [10], green investment [11], the consumption of renewable energies [12], globalization, income inequality and institutional quality [13], technological innovation [14], urban population growth [15], foreign direct investment [16], financial development and financial inclusion [17], policy uncertainty and geopolitical risk [18], human capital [19], oil price volatility and market uncertainty [20], natural resource rent [21], poverty alleviation strategies [22], and agricultural land expansion and deforestation [23]. However, it is still ambiguous how much damage environmental pollution causes and to what extent environmental technologies, energy efficiency, and renewable energy are effective in discerning the damage of environmental pollution.

Building on the above motivations, the primary objective of this study is to assess the damage for environmental pollution empirically and to give more insights into understanding the discerning effect of environmental technologies, energy efficiency, renewable energy, and natural resource rent within the context of "Organization for Economic Cooperation and Development (OECD)" economies during the period spanning 2000–2021. Examining the economic cost of environmental pollution for OECD economies is of great interest due to some rationales: (i) The OECD countries continued to contribute significantly to the worldwide production of energy generated from fossil fuels in 2021, accounting for 52% of the total. Furthermore, 42.2% of the world's electricity was generated in these nations in the same year. (ii) Although the OECD countries have committed to addressing climate change, there is reason for alarm as the financial burden of sustaining fossil fuels has more than doubled, surpassing 1.4 trillion dollars in 2022. (iii) OECD countries play a crucial role as significant contributors to atmospheric CO₂ emissions, representing one-third of the worldwide CO₂ emissions in 2020. In the same year, 8.1 metric tons of CO₂ were emitted per person in OECD countries [24]. Hence, it is imperative to identify viable strategies to accelerate the decarbonization process in these countries, as doing so is essential for mitigating the associated risks of climate issues.

There is widespread international evidence that environmental control technologies are the key enablers of the transition towards sustainable economies [8]. Lending support to this argument, several research studies concluded that environmental technologies are found to be effective in reversing environmental pollution caused by different sectors (energy, transport, commercial, residential, and manufacturing) [25–27]. However, contrary to the above argument, some evidence suggests that the development of environmental technologies can stimulate the demand for resource utilization as they reduce costs through an increase in energy efficiency [28]. Moreover, inappropriate, or weak environmental policies would promote the overexploitation of resources through the "rebound effect" and "green paradox" [29]. Further, economic growth is widely accepted as the major determinant of environmental quality in any nation. Since the seminal study conducted by Kuznets [30], the environmental Kuznets curve (EKC) hypothesis has become a theoretical ground that continues to guide the research on the economy–environment nexus. Contrarily, another spectrum of research contradicted the EKC postulation [31,32], suggesting that economic activities have an increasing effect on environmental pollution [33,34].

In this regard, a transition to renewable energy sources has been considered a milestone towards realizing the global climate goals [35,36]. For example, hydropower has gained more attention due to its clean production process and contribution to sustainable development that follows low maintenance costs, low operating expenses, and cost-effectiveness [37]. Contrary to this argument, Pata and Aydin [38] claimed that increasing

hydropower projects can extensively disrupt land and the natural flow of water. Despite this claim, it is generally acknowledged to have a favorable impact on environmental sustainability because of things like improved recreational options, flood control, and access to water [39]. Moreover, wind and solar power are economically sustainable due to their low installation cost but are prone to damage [3].

Further, natural resource rent and CO₂ emissions have been studied together under the purview of environmental sustainability by researchers who were also focused on economic development [40]. In this context, previous studies have provided significant evidence on how renewable resource consumption can reduce CO₂ emissions, mitigating the negative impact of natural resource rent [41,42]. Moreover, the synthesis of the relationship between energy efficiency and CO₂ emissions has led to significant insights. Numerous studies demonstrated that lower carbon emissions resulted from increased energy efficiency [43–46]. In comparison with non-OECD countries, OECD countries showed lesser energy efficiency in the period between the years 2000 and 2013. Only 3% of global energy consumption was saved in the process [45]. Technological advancements, along with efficiently diffused production technologies in OECD countries, have been instrumental in lowering CO₂ emissions and enhancing energy efficiency.

The existing research lacks work on carbon dioxide damage and its relationship with energy efficiency and other factors discussed above. On the other hand, the financial losses incurred due to carbon emissions have not been a significant part of the research conducted in this context of resource–emissions nexus. Thus, the current study aims to explore the influence of environmental technology, GDP, natural resource rents, renewable energy consumption, and energy efficiency on carbon damage.

This research adds to the body of literature in a few ways: Firstly, the existing literature has considered an indirect way of measuring the negative effect of atmospheric pollution through labor productivity and absenteeism at work, which leads to a reduction in per capita outputs [6,47–49]. However, using a direct measure that takes into consideration the heterogeneity across different regions and states could greatly improve our understanding of the financial damage caused by pollution. In this respect, we push the above strand of literature by using the adjusted savings- carbon dioxide damage quantified in present US dollars as the dependent variable.

Secondly, most of the existing literature has either centered on a single country-based analysis [50–52] or regional-based data investigation [53,54] with less focus on panel data analysis. Putting things in perspective, fighting against atmospheric pollution to reduce its financial cost requires an effective policy response based on a comprehensive scientific investigation, especially for countries that share some fiscal arrangements and common climate goals like OECD economies. Thus, this study's outcomes could greatly help in coordinating climate actions among the OECD countries.

Thirdly, the prior research extensively employed economic modeling, which focuses on contemporaneous air quality and economic output, excluding medium and longer-run influences. From this perspective, the generated output could underestimate the overall costs of atmospheric pollution [25,55]. Thus, for the sake of providing a more holistic time interval view of the financial cost of carbon emissions, this study employs the newly developed second-generation panel data technique, namely, the “Method of the Moments on Quantile Regression (MMQR)”.

2. Materials and Methods

2.1. Description of Data

This study undertakes a panel approach considering 22-year data (2000–2021) from the OECD countries to examine the impact of environmental control technology (EVT), renewable energy consumption (RWE), gross domestic product (GDP), natural resource rent (NRT), and energy efficiency (EFX) on carbon dioxide damage (CO₂D). Table 1 lists the variables along with their respective data sources.

Table 1. Description of variables.

Series	Notation	Unit of Measurement	Source
Carbon dioxide damage	CO ₂ D	Adjusted savings: carbon dioxide damage—current USD	Trading Economics (https://tradingeconomics.com/indicators , accessed on 15 July 2024)
Environmental technology	EVT	Number of patents for technologies used in environmental control	OECD (https://data.oecd.org/environment.htm , accessed on 15 July 2024)
Energy efficiency	EFX	Low carbon power use (TWh)	Our World in Data (https://ourworldindata.org/ , accessed on 15 July 2024)
Use of renewable energy	RWE	Percentage of final energy used	WDI (https://databank.worldbank.org/source/world-development-indicators , accessed on 15 July 2024)
Economic growth	GDP	Per capita GDP (USD 2015 constant)	WDI (https://databank.worldbank.org/source/world-development-indicators , accessed on 15 July 2024)
Natural resource rent	NRT	Proportion of GDP	WDI (https://databank.worldbank.org/source/world-development-indicators , accessed on 15 July 2024)

Note: WDI means World Development Indicators, GDP means Gross Domestic Product.

Here, CO₂D refers to adjusted savings carbon dioxide damage, which is a quantitative measure that determines the financial worth of the damage inflicted on the economy or environment because of carbon dioxide emissions. This tool computes the expenses linked to the detrimental consequences of carbon dioxide emissions on climate change, including elevated temperatures, rising sea levels, severe weather occurrences, and poor effects on human health and ecosystems. The adjusted savings carbon dioxide damage is quantified in present US dollars, so including the current currency valuation and reflecting on the assessment of harm resulting from carbon dioxide emissions is in relation to contemporary economic worth.

EVT is measured in terms of the number of patents on environmental control technologies, while RWE is calculated as the percentage of total energy use. GDP is the GDP per capita at the 2015 USD constant price, while NRT is measured as the proportion of the GDP. EFX refers to low-carbon energy consumption and is quantified in terawatt-hours of primary energy via the replacement technique. While data for RWE, GDP, and NRT were obtained from “World Development Indicators”, the data on energy efficiency have been extracted from the “Our World in Data” database. Since this study is confined to OECD countries, the data related to EVT were collected from the official OECD database.

2.2. Theoretical Background and Econometric Model

According to the general notion, the present study assumes that an increase in RWE and GDP growth enhances energy efficiency, leading to a decline in CO₂D [56]. Similarly, growing green innovation and investment in environmental control technologies can help mitigate CO₂ emissions released into the atmosphere [57]. Theoretically, technology innovation is hailed as a powerful weapon capable of balancing the old growth-centric paradigm with environmental sustainability [55]. Specifically, the energy technology adaptation has

the capacity to drive the shift towards a sustainable future, given its potential in combating the accumulation of gaseous emissions [25]. Empirically, the ecological modernization theory has been constantly fueling the research on the nexus between green technology innovation and environmental damage. This theory stresses that the environmental damage that stems from human activities can be neutralized by raising resource efficiency through the development of green technology. Given the high validity and the effectiveness of green technology in pollution abatement, many governments and enterprises have invested considerable resources in research and development to develop green and energy efficiency technologies [2].

Some authors argue that the adoption of renewable energy is difficult as its availability is dependent on weather conditions [58]. In the same context, GDP is highly influenced by external factors such as global financial crises, natural disasters, or pandemics. Weaker economies cannot afford the investment needed for green technology innovation, and they have to depend on technological transfer from high-income countries [59]. Thus, each variable comes with its favors and arguments towards carbon dioxide damage. Amidst these controversial findings of the existing literature, we considered each of the variables stated above in our proposed model. Accordingly, the model can be represented in equation form as follows:

$$\text{CO}_2\text{D} = f(\text{EVT}, \text{RWE}, \text{GDP}, \text{NRT}, \text{EFX}) \quad (1)$$

Here, CO_2D is the outcome variable. Since it is a panel framework, Equation (1) can be rewritten as the natural logarithmic value of each variable for better interpretation.

$$\ln\text{CO}_2\text{D}_{i,t} = \beta_0 + \beta_1 \ln\text{EVT}_{i,t} + \beta_2 \ln\text{RWE}_{i,t} + \beta_3 \ln\text{GDP}_{i,t} + \beta_4 \ln\text{NRT}_{i,t} + \beta_5 \ln\text{EFX}_{i,t} + \varepsilon_{i,t} \quad (2)$$

where i ($i = 1, 2, \dots, n$) represents the nation in the sample, and “ n ” = 38 (total number of OECD countries). Further, t ($t = 1, 2, \dots, N$) denotes the time period considered for this study (2000–2021). This study used STATA software 17 for analyzing the data.

2.3. Econometric Methodology

Now, we will discuss the econometric methodology adopted for this study in a step-by-step manner. The first step is to analyze “cross-sectional dependency (CSD)” among the variables considered for the panel study through the Pesaran [60] test. The next step is to trace the stationarity status of the variables to avoid ambiguous results between homogeneous and heterogeneous slope variables by using the Pesaran and Yamagata [61] “slope heterogeneity (SH)” test. Further, to confirm the findings of 2nd generation panel unit root tests, we used “cross-sectionally augmented Im-Pesaran-Shin (CIPS)” and “cross-sectional augmented Dickey–Fuller (CADF)” tests [62]. However, estimating the long-run coefficients requires identifying cointegrating associations among variables. The cointegrating association between the dependent and independent variables has been analyzed using Westerlund [63], Pedroni [64], and Kao [65] cointegration tests.

Finally, this study deployed the “Method of Moments Quantile Regression (MMQR)” introduced by Machado and Silva [66] to find the heterogeneity and distributional impacts across different quantiles. This approach includes the generalized median regression analysis across various quantiles. Given x_i is constant, the conditional quantile can be written y_i , as shown in Equation (3) below:

$$Q_{yi}(\tau | X_i) = x_i^T \beta_\tau. \quad (3)$$

Equation (3), however, does not permit unobserved heterogeneity. According to Cheng et al. [67] and Galvo [68], this heterogeneity may be supported by various econometric principles. To fit in the “panel quantile regression (PQR)” model, Equation (3) can be re-framed as follows:

$$Q_{yi}(\tau | \alpha_i, \chi_i) = \alpha_i + x'_{it} \beta(\tau_k) \quad (4)$$

The MMQR model suits well in nonlinear settings [55,69]. Furthermore, MMQR follows an exogenous method to define the threshold instead of a data-driven process [70]. Further, the approach was opted for because it addresses heterogeneity and endogeneity across variables, thereby providing more trustworthy results as compared to other PQR techniques. According to the study, the panel quantile function can be modified as follows:

$$Q_{yit}(\tau | \alpha_i, \zeta_i \chi_{it}) = \alpha_i + \zeta_i + \beta_{1t}EVT_{1t} + \beta_{2t}RWE_{2t} + \beta_{3t}GDP_{3t} + \beta_{4t}NRT_{4t} + \beta_{5t}EFX_{5t} \quad (5)$$

where y_{it} presents the CO₂D. The random probability is outlined as $P\{\delta_i + Z'_{it}\gamma > \tau\} = 1$. This further implies that:

$$CO_2D(\tau | X_{it}) = (\alpha_i + \delta_i q(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \quad (6)$$

where $q(\tau) = F_U^{-1}(\tau)$; thus, $P(U < q(\tau)) = \tau$. To address optimization problems concerning the sample quantile, the following equation is used:

$$\min_q \sum_i \sum_t \rho_\tau(A_{it} - (\delta_i + Z'_{it}\gamma)q) \quad (7)$$

Here, $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$ represents the check function.

Further, we deployed the “dynamic OLS (DOLS)” approach to check the reliability of the MMQR model. However, since the DOLS model does not consider the cross-sectional variability, we employed the “fully modified OLS (FMOLS)” proposed by Pedroni [64] as an alternative estimator for the cointegrated panels. Finally, we apply the “Driscoll–Kraay fixed-effect-OLS” framework to establish standard errors resistant to “autocorrelation, heteroscedasticity, and CSD”, as it considers heterogeneity across regions and time [71].

Finally, we used the “Dumirtescu and Hurlin (D-H) (2012) Granger panel causality” analysis to analyze the causality direction among variables. This test can be represented as follows:

$$y_{it} = \alpha_i + \sum_{j=1}^j \lambda_i^j y_{i(t-j)} + \sum_{j=1}^j \beta_i^j x_{i(t-j)} + \varepsilon_{it} \quad (8)$$

Figure 1 provides a graphical representation of the econometric modeling approach deployed in this study.

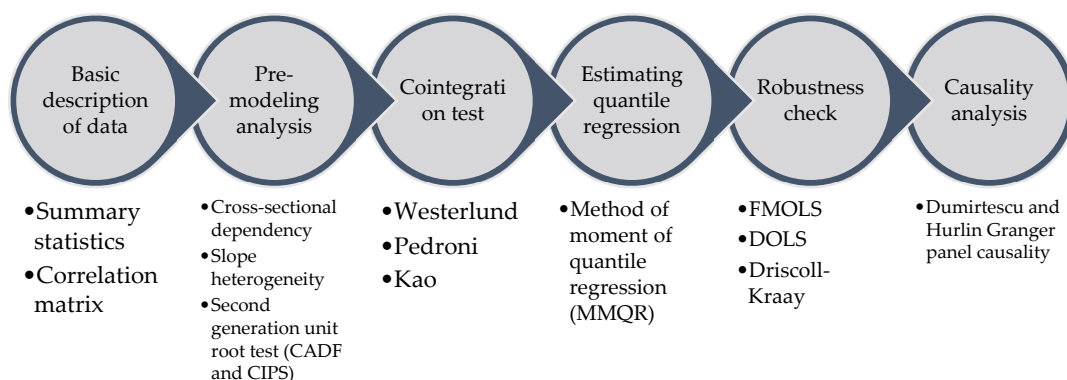


Figure 1. Econometric methodology process diagram of this study.

3. Results and Discussion

Table 2 represents the descriptive statistics and correlation matrix of the undertaken variables. It is evident that the mean (average) and median of all the variables are positive. Except for CO₂D and NRT, the variation spread (standard deviation) of all values stays below the mean. Apart from the GDP, all the variables have a right-hand tail distribution, based on the skewed values. We also conducted a kurtosis test to validate the likeliness of the existence of outliers or extreme values among variables. The results suggest that all the variables have significantly higher tails, different from the normal distribution, except the

GDP, whose value remains below the threshold point. The findings of the Jarque–Bera test and possibility values support these results. Based on these outcomes, it is necessary to tackle the non-normal distribution. Thus, we opted for deploying the MMQR approach, which is well suited to an asymmetric setting.

Table 2. Descriptive statistics and correlation matrix.

Stat.	CO ₂ D	EVT	RWE	GDP	NRT	EFX
Mean	16.111	10.490	19.162	10.149	1.459	21.701
Median	0.847	9.770	14.093	10.297	0.383	17.075
Maximum	701.200	72.730	78.214	11.724	21.418	82.835
Minimum	0.000	0.970	0.692	7.733	0.016	0.024
Std. Dev.	92.815	5.663	15.962	0.789	2.880	18.798
Skewness	6.042	3.689	1.295	−0.584	3.480	1.215
Kurtosis	38.034	34.366	4.568	2.839	17.302	4.028
Jarque–Bera	4566.740	34522.100	304.971	46.163	8412.637	231.348
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Correlation Matrix						
CO ₂ D	1.00					
EVT	−0.12	1.00				
RWE	−0.14	0.04	1.00			
GDP	0.02	−0.09	0.02	1.00		
NRT	−0.07	0.19	0.26	−0.14	1.00	
EFX	−0.19	−0.08	0.71	0.30	0.09	1.00

Note: All variables are in log form.

According to the correlation matrix, EVT and RWE are correlated with CO₂D negatively, while RWE is correlated with EVT positively. Further, the GDP is positively correlated with CO₂D and RWE. Moreover, NRT is negatively correlated with CO₂D and GDP while positively correlated with EVT and RWE. Finally, EFX is positively correlated with all the variables except CO₂D and EVT. From these results, it is evident that there is no multi-collinearity, suggesting that regression analysis does not have any spurious regressed outcomes.

The two issues of panel data, i.e., CSD and slope heterogeneity (SH), need to be explored before assessing the order of integration among the variables under study. CSD findings established in Table 3 demonstrate that none of the variables in the model have *p*-values greater than 0.05, signifying the rejection of the null hypothesis. At the 1% level of significance, cross-sections are not independent. It indicates that residuals across cross-sections are correlated. The average correlation coefficient of CO₂D represents a moderate positive correlation between cross-sectional units, which shows a moderate similarity in the behavior of CO₂D across different cross-sections. Contrary to that, the average absolute correlation of the CO₂D coefficient indicates a strong association across units irrespective of the direction of the association, hence supporting the evidence of CSD.

Table 3. CSD test.

Variable	CD-Test	<i>p</i> -Value	Corr.	Abs (Corr.)
CO ₂ D	55.617	0.000	0.46	0.58
EVT	45.293	0.000	0.37	0.47
RWE	57.859	0.000	0.48	0.72
GDP	103.182	0.000	0.85	0.85
NRT	35.196	0.000	0.29	0.44
EFX	37.556	0.000	0.31	0.55

Similarly, SH is considerable at the 1% level of significance, as revealed in Table 4. Referring to the SH test outcomes, the model has the issue of SH as depicted by both the substantial values of delta and the modified delta in static and HAC models. It accounts for the rejection of the null hypothesis that proposes the same slope of all series of variables. Thus, in this case, an alternative hypothesis must be accepted, which proposes heterogeneity in all series across all cross-sectional units. The results suggest that the association between CO₂D and other variables differs across cross-sectional units, so the assumption of the same slope is not valid here. Consequently, theoretical consequences of CSD coupled with slope heterogeneity of all coefficients in the model depict the rejection of first-generation unit root tests and call for the need for second-generation unit root tests to be applied for further analysis.

Table 4. SH Delta test.

Model: CO ₂ D = f (EVT, RWE, GDP, NRT, EFX)		Coeff.	p-Value
Static model	Δ	−10.655	0.000
	Δ adj.	−14.367	0.000
HAC model	Δ	−11.380	0.000
	Δ adj.	−16.535	0.000

Based on the CSD and SH test results in Tables 3 and 4, second-generation unit root tests are presented in Table 5. The 2nd generation CADF and CIPS tests account for potential problems associated with the panel data. The findings of CIPS and CADF specify that all variables have stationarity at first difference [I(1)]. Consequently, the findings of the CIPS unit root test specify the varying means and variances of the variables (CO₂D, EVT, RWE, GDP, NRT, and EFX). Hence, both cointegration test outcomes at the panel level of analysis show a significantly consistent and lasting link among variables of the model in Table 6.

Table 5. Unit root tests.

Variables	CIPS	CIPS 1st Difference	CADF	CADF 1st Difference
CO ₂ D	−2.216 **	−4.192 ***	−1.878	−2.313 ***
EVT	−3.130 ***	−4.833 ***	−2.952 ***	−3.551 ***
RWE	−2.176 **	−4.700 ***	−1.463	−3.615 ***
GDP	−1.937	−3.472 ***	−1.776	−2.546 ***
NRT	−2.206 **	−4.186 ***	−2.066 **	−3.679 ***
EFX	−2.219 **	−4.237 ***	−2.127 **	−3.196 ***

Note: ***, and ** indicate $p < 0.01$, and $p < 0.05$, respectively.

Table 6. Cointegration test outcomes.

Cointegration Tests	Statistic	p-Value
<i>Westerlund (2005) test</i>		
Variance Ratio	2.7617	0.000
<i>Pedroni (2001) test</i>		
Modified Phillips–Perron t	7.3779	0.000
Phillips–Perron t	−7.6916	0.000
Augmented Dickey–Fuller t	−6.5773	0.000
<i>Kao (1999) test</i>		
Modified Dickey–Fuller t	−4.5827	0.000
Dickey–Fuller t	−7.6754	0.000
Augmented Dickey–Fuller t	−8.8865	0.000
Unadjusted modified Dickey–Fuller t	−7.1161	0.000
Unadjusted Dickey–Fuller t''	−8.6517	0.000

Table 6 represents Westerlund [63], Pedroni [64], and Kao [65] cointegration tests. The Westerlund [63] test is statistically significant at 1% and suggests that variables under study have strong, stable long-term associations. Pedroni [64], in a similar manner, confirms the cointegration among all variables. The Kao [65] test justifies and corroborates these results and rejects the no cointegration null hypothesis. Therefore, all these tests give strong evidence of cointegration in the panel data, suggesting that variables have consistent and long-term associations.

From Table 7, it is found that EVT considerably influences CO₂D. EVT decreases CO₂D primarily in the first quantiles (5–20%) and more substantially in the grids of the medium quantiles (50% and 60%) but displays a more significant negative effect in upper quantiles (90% and 95%). The consistent negative sign shows that EVT decreases CO₂D across all parts of the distribution. This decrease shows that the impact of EVT is small in the lower quantiles, then high for medium quantiles, and largest for upper quantiles of CO₂D in the OECD countries. This intuition is consistent with the argument that EVTs tend to emit less CO₂ emissions, which means less damage due to carbon emissions. Ren et al. [4] state that clean technologies, along with technology spillover, help mitigate environmental pollution; however, the authors did not consider the financial damage due to carbon pollution. Similarly, Kocak and Alnour [2] prove the notion that environmental technologies improve resource efficiency that combats environmental pollution, which in turn reduces the financial damage due to carbon emissions. Therefore, EVTs are the key enablers in reducing CO₂ emission damage.

Table 7. MMQR outcomes.

Variable	Location	Scale	Quantiles										
			0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
EVT	−2.847 (2.384)	−1.474 ** (0.753)	−1.417 *** (0.341)	−1.596 *** (0.195)	−1.802 *** (0.448)	−1.995 ** (0.774)	−2.226 * (1.177)	−2.524 *** (0.703)	−2.886 *** (0.345)	−3.330 ** (1.436)	−4.157 * (2.630)	−6.955 *** (2.658)	−7.225 *** (2.328)
RWE	−0.230 *** (0.076)	−0.314 *** (0.004)	0.175 ** (0.080)	0.137 *** (0.023)	−0.288 *** (0.007)	−0.498 *** (0.048)	−0.098 * (0.058)	−0.161 * (0.110)	−0.238 ** (0.019)	−0.333 *** (0.069)	−0.510 *** (0.185)	−1.107 *** (0.429)	−2.444 *** (0.429)
GDP	21.246 *** (2.258)	7.407 *** (2.701)	4.058 *** (3.264)	4.959 *** (1.845)	5.996 *** (1.310)	6.968 *** (2.460)	8.127 *** (1.349)	8.625 *** (1.429)	9.443 *** (2.621)	9.677 *** (2.247)	9.832 *** (4.309)	9.900 *** (2.736)	10.415 *** (3.943)
NRT	1.859 (4.211)	1.294 (4.863)	0.604 (0.618)	0.764 (0.649)	0.942 (0.816)	1.112 (1.413)	1.315 (2.150)	1.576 (3.112)	1.894 (1.285)	2.284 (1.730)	3.010 (2.430)	3.468 (2.564)	3.973 (3.226)
EFX	−1.027 *** (0.190)	−0.476 (1.375)	−0.565 *** (0.174)	−0.623 *** (0.099)	−0.689 *** (0.230)	−0.752 * (0.398)	−1.826 ** (0.605)	−1.922 ** (0.876)	−1.039 *** (0.207)	−2.183 * (1.114)	−2.450 *** (0.375)	−2.354 ** (1.048)	−3.380 * (1.790)
_cons	223.722 *** (14.034)	101.626 *** (47.138)	125.103 *** (31.207)	137.467 *** (17.703)	151.703 *** (41.137)	165.030 ** (71.191)	180.935 * (108.282)	201.488 * (106.731)	226.432 * (115.787)	257.085 * (158.538)	314.082 ** (124.945)	307.092 ** (185.506)	339.473 ** (193.384)

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively. The value in the parenthesis is the standard error.

Similarly, RWE has a negative correlation with CO₂D, which is significantly heterogeneous in all grids of quantiles. The empirical estimates portray that more use of renewable energy sources shields the natural ecosystem and leaves lower carbon emissions [35]. For example, the result shows that RWE decreases CO₂D by 0.098% at the 40th quantile. All quantiles are inversely associated with CO₂D as RWE releases less CO₂ during production processes. Hence, upper quantiles are highly significant with large coefficients. This finding indicates that increased use of RWE can reduce CO₂D for large-change and small-change in RWE. The results suggest that the use of renewable energy sources such as biofuel, solar and wind energy, nuclear energy, and hydropower energy can improve environmental sustainability by reducing CO₂ emissions [2,38] as well as financial damage by carbon emissions. Nonetheless, the results of this study are distinct from other research since they did not regard the financial repercussions of carbon emissions in the OECD region as the dependent variable.

Across all grids of MMQR quantiles, there is a positive and robust association between GDP and CO₂D, indicating that rising economic growth is bad for the environment since it raises financial damage costs. The coefficients become large as they move towards upper quantiles. Small-change countries represent less-developed OECD countries as compared to high-income nations. Therefore, small-change countries are still relying on secondary industries, and, hence, their rising GDP will enhance CO₂D by large. Cheng et al. [71] assert that the majority of OECD countries adhere to quantity-oriented development models that neglect carbon mitigation techniques and financial damage due to carbon emission assessment methods for this region. Moreover, the increasing rate of economic growth

along with increasing CO₂D in upper quantiles shows the worsening state of the OECD environment; the governments of OECDs changed their growth patterns from extensive to intensive development.

NRT is insignificant across all quantiles, suggesting that the association between NRT and CO₂D is complex and may not be observable across all levels of CO₂D in OECD nations. Although NRT is insignificant, a positive sign suggests that NRT upsurges CO₂D. This finding indicates that the rent-seeking impact on natural resources is hazardous to the OECD environment, which raises CO₂D. Moreover, these rents further provide incentives to explore further resources and generate rent that add more harm to the environment. These results align with earlier research, such as that conducted by Ibrahim and Ajide [72].

Additionally, EFX considerably affects CO₂D across all quantiles. EFX declines CO₂D mainly in the first quantiles (5–20%) and more substantially in the grids of the medium quantile (60%) but demonstrates a higher negative and significant influence in upper quantiles (80%). Tajudeen et al. [46] signify that OECD countries show a downward trend in the energy intensity index; hence, large-change OECD nations may need a more efficient use of energy mix, which can reduce the financial damage of carbon emissions. EFX helps to improve environmental sustainability and reduce environmental harm by lowering the dependency on fossil fuels and, in turn, reducing carbon emissions. Thus, EFX seems to reduce CO₂D and enhance environmental quality by sustaining energy in transport, building operations, and other sectors. A similar outcome is reported by Wenlong et al. [73].

Figure 2 shows a graphical representation of quantile coefficients. MMQR coefficients divulge considerable differences among quantiles, which is further supported by significant location and scale factors in Table 7. At lower quantiles, the effect of EVT is consistent, yet this impact becomes more pronounced at higher quantiles, indicated by a downward slope and wide confidence interval. Similarly, RWE is consistent across lower grids yet its impact increases at higher grids. GDP and NRT are positive, yet GDP becomes more substantial at upper quantiles, indicating that higher economic growth asserts a more pronounced impact on CO₂D. Contrarily, EFX is minimal across lower quantiles, yet its impact becomes more at higher quantiles. Wang and Wei [74] argue that OECD nations contribute 85% of global CO₂ emissions globally. Therefore, these nations must shoulder the responsibility to mitigate it. CO₂D is higher when OECD nations are at higher levels of economic growth and generating more rent through the extraction of natural resources. A country's government will prioritize environmental sustainability issues when its income level is high enough. Examples of this activity include sponsoring R&D on green environmental technologies and passing legislation to safeguard the environment. CO₂D is lowest when OECD nations use more environmental technologies, renewable energy sources, and energy efficiency measures.

For a robustness check, this study uses FMOLS, DOLS, and Driscoll-Kraay estimators. Philips and Hansen [75] point out that FMOLS tackle endogeneity and control serial correlation among explanatory factors due to the high parametric efficiency of small samples. As for DOLS, Stock and Watson [76] state that DOLS gives robust estimates for small samples and controls endogeneity for regressors by using leads and lags of the first difference in regressors by removing the bias of simultaneity. Similarly, Driscoll-Kraay [77] is used as an additional estimator for robustness. Driscoll-Kraay standard errors can handle CSD due to their robust nature to spatial and temporal dependence. Hence, Driscoll-Kraay can produce heteroskedastic and autocorrelated consistent standard errors [78,79].

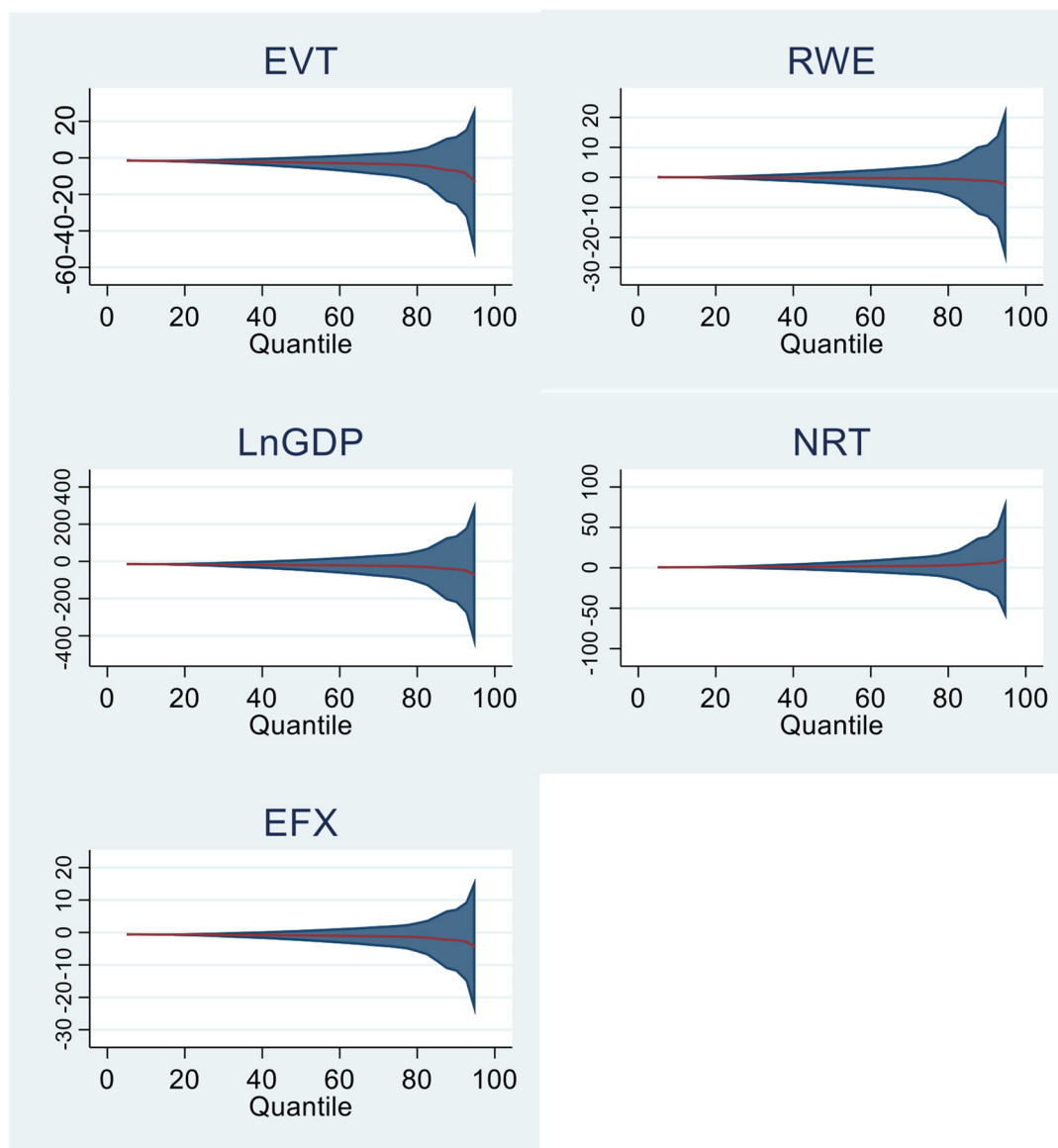


Figure 2. Graphical display of panel quantile outcomes.

Table 8 presents the results of the robustness check with the dependent variable as CO₂D. All estimators suggest that EVT has a negative and significant impact on CO₂D, yet Driscoll–Kraay shows a more pronounced impact. This result suggests that holding all other things equal, EVT has a favorable impact on reducing CO₂ emission damage in OECD nations. Similar outcomes can be seen in RWE and EFX for the reduction in CO₂D. Yet, GDP and NRT boost this impact. Driscoll–Kraay shows NRT significance after controlling endogeneity. However, these results seem to communicate that MMQR results are robust.

Table 8. Robustness results.

Variable	FMOLS	DOLS	Driscoll–Kraay
EVT	−0.164 *	−1.018 *	−2.847 ***
RWE	−0.299 **	−0.257 *	−0.229 **
GDP	1.572 ***	1.991 ***	3.246 ***
NRT	0.014	0.602	1.859 *
EFX	−0.129 **	−0.715 *	−1.027 ***

Note: ***, **, and * indicate $p < 0.01$, $p < 0.05$, and $p < 0.1$, respectively.

The results of the Granger test of the causal relationship between the variables under investigation for the OECD nations are shown in Table 9. The findings suggest that all variables have a unidirectional Granger causal connection with CO₂D. The null hypothesis of the causality is homogeneous across all OECD nations in the panel set and is tested; hence, it is rejected at 5% and 10% levels for EVT, RWE, GDP, NRT, and EFX with CO₂D. The results imply that there is a unidirectional causal relationship among all variables. Hence, unidirectional causality implies that all variables Granger-cause CO₂D, yet CO₂D does not impact any of them directly.

Table 9. D–H causality test results.

Relation	F-Statistic	Prob.
EVT → CO ₂ D	2.593	0.076
CO ₂ D → EVT	0.338	0.713
RWE → CO ₂ D	7.160	0.001
CO ₂ D → RWE	1.761	0.173
GDP → CO ₂ D	2.383	0.082
CO ₂ D → GDP	0.158	0.854
NRT → CO ₂ D	2.560	0.076
CO ₂ D → NRT	0.036	0.965
EFX → CO ₂ D	2.771	0.073
CO ₂ D → EFX	0.159	0.853

Note: → means the null hypothesis states that the variable does not Granger-cause other variables.

4. Conclusions and Policy Implications

With the rise in industrialization, a rise in carbon damage has also been witnessed. Among various factors affecting damage caused by carbon emissions, this study considered environmental-related technologies, renewable energy consumption, natural resource rent, energy efficiency, and the GDP. The 22-year (2000–2021) data collected from OECD countries were analyzed using the “Method of Moments Quantile Regression (MMQR)” to examine the impact of the considered variables on environmental damage. The findings stated that a 1% increase in EVT consistently helps in reducing carbon emissions damage in the OECD countries by 1.417% to 7.225%. It was noted that the association between GDP and CO₂D is positive in all quantiles, which indicates that economic growth worsens the environmental cost of the OECD by 4.058% to 10.415% for a 1% increase in GDP. Further, a 1% rise in renewable energy consumption results in a 0.098–2.444% reduction in carbon emission damage. Moreover, energy efficiency helps in declining the financial damage caused by carbon emissions released into the environment, while the impact of natural resource rent is insignificant. Different robustness checks also reported similar results; hence, the MMQR findings are robust for policy ramifications.

4.1. Policy Implications

The findings of this study suggest some policy recommendations that can be beneficial to industries and countries under the context of environmental protection from carbon damage.

The findings state that EVT supports reducing carbon emission damage in the OECD countries. Industrial activities in OECD economies contribute substantially to CO₂D; hence the adoption of environmental control methods and technologies is crucial. Consequently, governments should invest in R&D activities to implement carbon capture and storage technologies in heavy and medium-term industries. Similarly, industries should be forced to implement greener operations through technology transfer agreements and global partnership programs. The implementation of these programs and agreements requires regulatory frameworks that compel us to adopt stringent environmental practices to accelerate decarbonization.

It is observed that RWE is used to decarbonize the OECD economies; still, there is room to adopt renewable sources for further improvement. Policymakers must subsidize

renewable energy projects to promote the use of solar, wind, and other renewable sources at industrial and residential scales. Therefore, to increase the use of clean energy solutions, tax incentives and grants should be given, and governments must invest in energy grid infrastructure for energy security. Moreover, global cooperation for renewable energy technology exchange can expedite the process and leverage OECDs to save the environment from carbon damage. Similarly, energy efficiency principles need to be implemented across agriculture, industrial, and transport sectors by providing financial incentives.

The significant positive association between GDP and CO₂D suggests the need to decouple the growth of the economy from environmental damage. Governments and policymakers need to put their focus on low-emitting sectors such as digital technology and biotechnology that do not significantly contribute to emissions. The circular economy model as a solution can help mitigate waste by recycling and reusing resources to reduce carbon footprints. The reduction in carbon damage can be further encouraged through policy interventions like carbon pricing. The incentivization of reduced carbon footprints can become integral to businesses if the costs are internalized based on taxations pertaining to carbon emissions.

4.2. Limitations and Future Research Direction

This research carries several limitations. For example, the secondary data used in this study may be biased. This study fails to provide an accurate picture of the financial risks and costs for energy transitions undertaken by the OECD countries. Furthermore, because this study was limited to only OECD countries, a comprehensive understanding of the current research context is lacking. For example, there is a requirement for the creation and streamlining of policy portfolios for EVT and carbon pricing across jurisdictions of OECD countries to engage industries seamlessly in energy-efficient practices. Since the current research is restricted to OECD countries, it may benefit to include the EU and other allied nations as they are all trade partners in sustainability practices. Country-wise or case-specific studies can bring greater insights into the research context as the intervening variables like policies, rebates, the scale of the industry, and energy dependencies vary across sectors and nations.

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References

1. 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. [[CrossRef](#)]
2. Kocak, E.; Alnour, M. Energy R&D Expenditure, Bioethanol Consumption, and Greenhouse Gas Emissions in the United States: Non-Linear Analysis and Political Implications. *J. Clean. Prod.* **2022**, *374*, 133887. [[CrossRef](#)]
3. Perone, G. The Relationship between Renewable Energy Production and CO₂ Emissions in 27 OECD Countries: A Panel Cointegration and Granger Non-Causality Approach. *J. Clean. Prod.* **2024**, *434*, 139655. [[CrossRef](#)]

4. Ren, S.; Du, M.; Bu, W.; Lin, T. Assessing the Impact of Economic Growth Target Constraints on Environmental Pollution: Does Environmental Decentralization Matter? *J. Environ. Manag.* **2023**, *336*, 117618. [CrossRef] [PubMed]
5. Kassouri, Y. Monitoring the Spatial Spillover Effects of Urbanization on Water, Built-up Land and Ecological Footprints in Sub-Saharan Africa. *J. Environ. Manag.* **2021**, *300*, 113690. [CrossRef]
6. Dechezleprêtre, A.; Rivers, N.; Stadler, B. The Economic Cost of Air Pollution: Evidence from Europe. In *OECD Economics Department Working Papers*; OECD Publishing: Paris, France, 2019. [CrossRef]
7. Feng, T.; Chen, X.; Ma, J.; Sun, Y.; Du, H.; Yao, Y.; Chen, Z.; Wang, S.; Mi, Z. Air Pollution Control or Economic Development? Empirical Evidence from Enterprises with Production Restrictions. *J. Environ. Manag.* **2023**, *336*, 117611. [CrossRef]
8. Mongo, M.; Belaïd, F.; Ramdani, B. The Effects of Environmental Innovations on CO₂ Emissions: Empirical Evidence from Europe. *Environ. Sci. Policy* **2021**, *118*, 1–9. [CrossRef]
9. Tolliver, C.; Keeley, A.R.; Managi, S. Policy Targets behind Green Bonds for Renewable Energy: Do Climate Commitments Matter? *Technol. Forecast. Soc. Change* **2020**, *157*, 120051. [CrossRef]
10. Caglar, A.; Zafar, M.; Bekun, F.; Mert, M. Determinants of CO₂ Emissions in the BRICS Economies: The Role of Partnerships Investment in Energy and Economic Complexity. *Sustain. Energy Technol. Assess.* **2022**, *51*, 101907. [CrossRef]
11. Huang, Y.; Xue, L.; Khan, Z. What Abates Carbon Emissions in China: Examining the Impact of Renewable Energy and Green Investment. *Sustain. Dev.* **2021**, *29*, 823–834. [CrossRef]
12. Kuldasheva, Z.; Salahodjaev, R. Renewable Energy and CO₂ Emissions: Evidence from Rapidly Urbanizing Countries. *J. Knowl. Econ.* **2023**, *14*, 1077–1090. [CrossRef]
13. Jahanger, A.; Usman, M.; Balsalobre-Lorente, D. Linking Institutional Quality to Environmental Sustainability. *Sustain. Dev.* **2022**, *30*, 1749–1765. [CrossRef]
14. Obobisa, E.S. Achieving 1.5 °C and Net-Zero Emissions Target: The Role of Renewable Energy and Financial Development. *Renew. Energy* **2022**, *188*, 967–985. [CrossRef]
15. 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]
16. Chi, F.; Meng, Z. The Effects of ICT and FDI on CO₂ Emissions in China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 3133–3145. [CrossRef]
17. Abid, A.; Mehmood, U.; Tariq, S.; Haq, Z.U. The Effect of Technological Innovation, FDI, and Financial Development on CO₂ Emission: Evidence from the G8 Countries. *Environ. Sci. Pollut. Res.* **2022**, *29*, 11654–11662. [CrossRef]
18. Nakhli, M.S.; Shahbaz, M.; Ben Jebli, M.; Wang, S. Nexus between Economic Policy Uncertainty, Renewable & Non-Renewable Energy and Carbon Emissions: Contextual Evidence in Carbon Neutrality Dream of USA. *Renew. Energy* **2022**, *185*, 75–85. [CrossRef]
19. Xu, X.; Huang, S.; An, H. Identification and Causal Analysis of the Influence Channels of Financial Development on CO₂ Emissions. *Energy Policy* **2021**, *153*, 112277. [CrossRef]
20. Malik, M.; Latif, K.; Khan, Z.; Butt, H.; Hussain, M. Symmetric and Asymmetric Impact of Oil Price, FDI and Economic Growth on Carbon Emission in Pakistan: Evidence from ARDL and Non-Linear ARDL Approach. *Sci. Total Environ.* **2020**, *726*, 138421. [CrossRef]
21. Tufail, M.; Song, L.; Adebayo, T.S.; Kirikkaleli, D.; Khan, S. Do Fiscal Decentralization and Natural Resources Rent Curb Carbon Emissions? Evidence from Developed Countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 49179–49190. [CrossRef]
22. Fu, R.; Jin, G.; Chen, J. The Effects of Poverty Alleviation Investment on Carbon Emissions in China Based on the Multiregional Input–Output Model. *Technol. Forecast. Soc. Change* **2021**, *162*, 120344. [CrossRef]
23. Raihan, A.; Begum, R.; Nizam, M.; Said, M.; Pereira, J. Dynamic Impacts of Energy Use, Agricultural Land Expansion, and Deforestation on CO₂ Emissions in Malaysia. *Environ. Ecol. Stat.* **2022**, *29*, 477–507. [CrossRef]
24. Ritchie, H.; Roser, M. CO₂ and Greenhouse Gas Emissions. Our World in Data 2020. Available online: <https://ourworldindata.org/co2-and-greenhouse-gas-emissions> (accessed on 15 July 2024).
25. Awan, A.; Abbasi, R.; Rej, S.; Bandyopadhyay, A.; Lv, K. The Impact of Renewable Energy, Internet Use and Foreign Direct Investment on Carbon Dioxide Emissions: A Method of Moments Quantile Analysis. *Renew. Energy* **2022**, *189*, 454–466. [CrossRef]
26. Bekun, F.V. Race to Carbon Neutrality in South Africa: What Role Does Environmental Technological Innovation Play? *Appl. Energy* **2024**, *354*, 122212. [CrossRef]
27. Zakari, A.; Khan, I. The Impact of Environmental Technology Innovation and Energy Credit Rebate on Carbon Emissions: A Comparative Analysis. *J. Int. Dev.* **2023**, *35*, 2609–2625. [CrossRef]
28. Zhang, J.; Lawell, C. The Macroeconomic Rebound Effect in China. *Energy Econ.* **2017**, *67*, 202–212. [CrossRef]
29. Ulucak, R.; Danish; Kassouri, Y. An Assessment of the Environmental Sustainability Corridor: Investigating the Non-Linear Effects of Environmental Taxation on CO₂ Emissions. *Sustain. Dev.* **2020**, *28*, 1010–1018. [CrossRef]
30. Kuznets, S. Economic Growth and Income Inequality. *Am. Econ. Rev.* **1995**, *45*, 25–37.
31. Rahman, M.M.; Nepal, R.; Alam, K. Impacts of Human Capital, Exports, Economic Growth and Energy Consumption on CO₂ Emissions of a Cross-Sectionally Dependent Panel: Evidence from the Newly Industrialized Countries (NICs). *Environ. Sci. Policy* **2021**, *121*, 24–36. [CrossRef]
32. Peng, Z.; Wu, Q.; Li, M. Spatial Characteristics and Influencing Factors of Carbon Emissions from Energy Consumption in China's Transport Sector: An Empirical Analysis Based on Provincial Panel Data. *Pol. J. Environ. Stud.* **2020**, *29*, 217–232. [CrossRef]

33. Shahbaz, M.; Haouas, I.; Hoang, T.H. Van Economic Growth and Environmental Degradation in Vietnam: Is the Environmental Kuznets Curve a Complete Picture? *Emerg. Mark. Rev.* **2019**, *38*, 197–218. [\[CrossRef\]](#)
34. Sterpu, M.; Soava, G.; Mehedintu, A. Impact of Economic Growth and Energy Consumption on Greenhouse Gas Emissions: Testing Environmental Curves Hypotheses on EU Countries. *Sustainability* **2018**, *10*, 3327. [\[CrossRef\]](#)
35. Magazzino, C.; Mele, M.; Schneider, N.; Shahbaz, M. Can Biomass Energy Curtail Environmental Pollution? A Quantum Model Approach to Germany. *J. Environ. Manage* **2021**, *287*, 112293. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Javed, S.; Zhu, B.; Liu, S. Forecast of Biofuel Production and Consumption in Top CO₂ Emitting Countries Using a Novel Grey Model. *J. Clean. Prod.* **2020**, *276*, 123997. [\[CrossRef\]](#)
37. Lau, E.; Tan, C.C.; Tang, C.F. Dynamic Linkages among Hydroelectricity Consumption, Economic Growth, and Carbon Dioxide Emission in Malaysia. *Energy Sources Part B Econ. Plan. Policy* **2016**, *11*, 1042–1049. [\[CrossRef\]](#)
38. Pata, U.K.; Aydin, M. Testing the EKC Hypothesis for the Top Six Hydropower Energy-Consuming Countries: Evidence from Fourier Bootstrap ARDL Procedure. *J. Clean. Prod.* **2020**, *264*, 121699. [\[CrossRef\]](#)
39. Alnour, M.; Ali, M.; Abdalla, A.; Abdelrahman, R.; Khalil, H. How Do Urban Population Growth, Hydropower Consumption and Natural Resources Rent Shape Environmental Quality in Sudan? *World Dev. Sustain.* **2022**, *1*, 100029. [\[CrossRef\]](#)
40. Achuo, E.D.; Miamo, C.W.; Kouhomou, C.Z. Resource Rents and Environmental Pollution in Developing Countries: Does the Quality of Institutions Matter? *Rev. Dev. Econ.* **2024**, *28*, 360–387. [\[CrossRef\]](#)
41. Zhang, X.; Shi, X.; Khan, Y.; Khan, M.; Naz, S.; Hassan, T.; Wu, C.; Rahman, T. The Impact of Energy Intensity, Energy Productivity and Natural Resource Rents on Carbon Emissions in Morocco. *Sustainability* **2023**, *15*, 6720. [\[CrossRef\]](#)
42. Shen, Y.; Su, Z.; Malik, M.; Umar, M.; Khan, Z. Does Green Investment, Financial Development and Natural Resources Rent Limit Carbon Emissions? A Provincial Panel Analysis of China. *Sci. Total Environ.* **2021**, *755*, 142538. [\[CrossRef\]](#)
43. Iram, R.; Zhang, J.; Erdogan, S.; Abbas, Q. Economics of Energy and Environmental Efficiency: Evidence from OECD Countries. *Environmental Sci. Pollut. Res.* **2020**, *27*, 3858–3870. [\[CrossRef\]](#) [\[PubMed\]](#)
44. Kim, K.; Kim, Y. International Comparison of Industrial CO₂ Emission Trends and the Energy Efficiency Paradox Utilizing Production-Based Decomposition. *Energy Econ.* **2012**, *34*, 1724–1741. [\[CrossRef\]](#)
45. Liddle, B.; Sadorsky, P. Energy Efficiency in OECD and Non-OECD Countries: Estimates and Convergence. *Energy Effic.* **2021**, *14*, 72. [\[CrossRef\]](#)
46. Tajudeen, I.A.; Wossink, A.; Banerjee, P. How Significant Is Energy Efficiency to Mitigate CO₂ Emissions? Evidence from OECD Countries. *Energy Econ.* **2018**, *72*, 200–221. [\[CrossRef\]](#)
47. Fan, M.; Grainger, C. The Impact of Air Pollution on Labor Supply in China. *Sustainability* **2023**, *15*, 13082. [\[CrossRef\]](#)
48. Wu, B.; Yan, T.; Elahi, E. The Impact of Environmental Pollution on Labor Supply: Empirical Evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 25764–25772. [\[CrossRef\]](#) [\[PubMed\]](#)
49. Orellano, P.; Reynoso, J.; Quaranta, N. Effects of Air Pollution on Restricted Activity Days: Systematic Review and Meta-Analysis. *Environ. Health* **2023**, *22*, 31. [\[CrossRef\]](#)
50. Chen, F.; Chen, Z. Cost of Economic Growth: Air Pollution and Health Expenditure. *Sci. Total Environ.* **2021**, *755*, 142543. [\[CrossRef\]](#)
51. Meisner, C.; Gjorgjev, D.; Tozija, F. Estimating Health Impacts and Economic Costs of Air Pollution in the Republic of Macedonia. *South East. Eur. J. Public Health* **2023**. [\[CrossRef\]](#)
52. Pandey, A.; Brauer, M.; Cropper, M.L.; Balakrishnan, K.; Mathur, P.; Dey, S.; Turkoglu, B.; Kumar, G.A.; Khare, M.; Beig, G.; et al. Health and Economic Impact of Air Pollution in the States of India: The Global Burden of Disease Study 2019. *Lancet Planet Health* **2021**, *5*, e25–e38. [\[CrossRef\]](#)
53. Font-Ribera, L.; Rico, M.; Marí-Dell’Olmo, M. Estimating Ambient Air Pollution Mortality and Disease Burden and Its Economic Cost in Barcelona. *Environ. Res.* **2023**, *216*, 114485. [\[CrossRef\]](#) [\[PubMed\]](#)
54. Ugochukwu, U.C.; Chukwuone, N.; Jidere, C.; Ezeudu, B.; Ikpo, C.; Ozor, J. Heavy Metal Contamination of Soil, Sediment and Water Due to Galena Mining in Ebonyi State Nigeria: Economic Costs of Pollution Based on Exposure Health Risks. *J. Environ. Manage* **2022**, *321*, 115864. [\[CrossRef\]](#) [\[PubMed\]](#)
55. Awan, A.; Alnour, M.; Jahanger, A.; Onwe, J.C. Do Technological Innovation and Urbanization Mitigate Carbon Dioxide Emissions from the Transport Sector? *Technol. Soc.* **2022**, *71*, 102128. [\[CrossRef\]](#)
56. Akram, R.; Majeed, M.T.; Fareed, Z.; Khalid, F.; Ye, C. Asymmetric Effects of Energy Efficiency and Renewable Energy on Carbon Emissions of BRICS Economies: Evidence from Nonlinear Panel Autoregressive Distributed Lag Model. *Environ. Sci. Pollut. Res.* **2020**, *27*, 18254–18268. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Suki, N.M.; Suki, N.M.; Sharif, A.; Afshan, S.; Jermisittiparsert, K. The Role of Technology Innovation and Renewable Energy in Reducing Environmental Degradation in Malaysia: A Step towards Sustainable Environment. *Renew. Energy* **2022**, *182*, 245–253. [\[CrossRef\]](#)
58. Russo, M.A.; Carvalho, D.; Martins, N.; Monteiro, A. Forecasting the Inevitable: A Review on the Impacts of Climate Change on Renewable Energy Resources. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102283. [\[CrossRef\]](#)
59. Ferreira, J.; Fernandes, C.; Ferreira, F. Technology Transfer, Climate Change Mitigation, and Environmental Patent Impact on Sustainability and Economic Growth: A Comparison of European Countries. *Technol. Forecast. Soc. Change* **2020**, *150*, 11970. [\[CrossRef\]](#)

60. Pesaran, M. A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence. *J. Appl. Econom.* **2007**, *22*, 265–312. [[CrossRef](#)]
61. Pesaran, M.; Yamagata, T. Testing Slope Homogeneity in Large Panels. *J. Econom.* **2008**, *142*, 50–93. [[CrossRef](#)]
62. Pesaran, M.H. General Diagnostic Tests for Cross Section Dependence in Panels. *Economics* **2004**, *1240*, 1. [[CrossRef](#)]
63. Westerlund, J. New Simple Tests for Panel Cointegration. *Econom. Rev.* **2005**, *24*, 297–316. [[CrossRef](#)]
64. Pedroni, P. Fully Modified OLS for Heterogeneous Cointegrated Panels. In *Advances in Econometrics*; JAI Press: Stamford, CT, USA, 2001; Volume 15, pp. 93–130, ISBN 0762306882.
65. Kao, C. Spurious Regression and Residual-Based Tests for Cointegration in Panel Data. *J. Econom.* **1999**, *90*, 1–44. [[CrossRef](#)]
66. Machado, J.A.F.; Santos Silva, J.M.C. Quantiles via Moments. *J. Econom.* **2019**, *213*, 145–173. [[CrossRef](#)]
67. Cheng, C.; Ren, X.; Dong, K.; Dong, X.; Wang, Z. How Does Technological Innovation Mitigate CO₂ Emissions in OECD Countries? Heterogeneous Analysis Using Panel Quantile Regression. *J. Environ. Manage* **2021**, *280*, 111818. [[CrossRef](#)] [[PubMed](#)]
68. Galvao, A. Quantile Regression for Dynamic Panel Data with Fixed Effects. *J. Econom.* **2011**, *164*, 142–157. [[CrossRef](#)]
69. Shin, Y.; Yu, B.; Greenwood-Nimmo, M. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. In *Festschrift in Honor of Peter Schmidt: Econometric Methods and Application*; Springer: New York, NY, USA, 2014; pp. 281–314.
70. Gyamfi, B.; Adebayo, T. Do Natural Resource Volatilities and Renewable Energy Contribute to the Environment and Economic Performance? Empirical Evidence from E7 Economies. *Environ. Sci. Pollut. Res.* **2023**, *30*, 19380–19392. [[CrossRef](#)]
71. Cheng, C.; Ren, X.; Wang, Z. The Impact of Renewable Energy and Innovation on Carbon Emission: An Empirical Analysis for OECD Countries. *Energy Procedia* **2019**, *158*, 3506–3512. [[CrossRef](#)]
72. Ibrahim, R.; Ajide, K. The Dynamic Heterogeneous Impacts of Nonrenewable Energy, Trade Openness, Total Natural Resource Rents, Financial Development and Regulatory Quality. *Resour. Policy* **2021**, *74*, 102251. [[CrossRef](#)]
73. Wenlong, Z.; Tien, N.; Sibghatullah, A.; Asih, D. Impact of Energy Efficiency, Technology Innovation, Institutional Quality, and Trade Openness on Greenhouse Gas Emissions in Ten Asian Economies. *Environ. Sci. Pollut. Res.* **2023**, *30*, 43024–43039. [[CrossRef](#)]
74. Wang, H.; Wei, W. Coordinating Technological Progress and Environmental Regulation in CO₂ Mitigation: The Optimal Levels for OECD Countries & Emerging Economies. *Energy Econ.* **2020**, *87*, 104510.
75. Phillips, P.; Hansen, B. Statistical Inference in Instrumental Variables Regression with I(1) Processes. *Rev. Econ. Stud.* **1990**, *57*, 99–125. [[CrossRef](#)]
76. Stock, J.; Watson, M. A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems. *Econometrica* **1993**, *61*, 783–820. [[CrossRef](#)]
77. Driscoll, J.; Kraay, A. Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Rev. Econ. Stat.* **1998**, *80*, 549–560. [[CrossRef](#)]
78. Hoechle, D. Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence. *Stata J.* **2007**, *7*, 281–312. [[CrossRef](#)]
79. De Hoyos, R.E.; Sarafidis, V. Testing for Cross-Sectional Dependence in Panel-Data Models. *Stata J.* **2006**, *6*, 482–496. [[CrossRef](#)]

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