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The Impact of Technology and Government Policies on OECD Carbon Dioxide Emissions

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Abstract: This study investigated the effect of technology and government policies on carbon dioxide (CO_2) emissions in 36 Organisation for Economic Co-operation and Development (OECD) countries from 1994 to 2015. This empirical investigation uses econometric models, such as panel quantile regression and ordinary least squares (OLS). The research uses the method proposed by Lin and Ng in 2015 to deal with parameter heterogeneity across countries that identified two separate groups. The empirical results indicated that Gross Domestic Product (GDP), fossil fuel consumption, industrialisation and taxation to GDP intensify CO_2 emissions. In contrast, urbanisation (% of the total population), environmental patents, and environmental tax as a percentage of total tax reduce CO_2 gas emissions. Estimates with homogeneity preserve the signs of the parameters but reveal substantial differences in intensity and that environmental tax revenues (as % of GDP and % of tax) are only statistically significant for our studied group 1. The conclusions of this study have important policy implications. The effect of industrialisation on environmental degradation is an observable fact. When the country reaches the allowable thresholds, it needs to maximize energy consumption. Policymakers should design policies that help them to promote environmentally sustainable economic growth by imposing and accumulating environmental taxes. In addition, environmental taxes, the discharge system and credit could support the modification of in-industrial structures and modes of economic growth. Policymakers should also use policies that encourage trade in nuclear-generated electricity to neighbouring OECD countries.

Keywords: carbon dioxide emissions; patents on environment technologies; environmental tax revenue; economic policy; OECD countries

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1. Introduction

Nations around the world have realised the threat of global warming, and since the Paris climate agreement, most economies have submitted their planned national plans to clarify mitigation strategies, showing the Intended Nationally Determined Contributions (INDC). Even though these INDCs reflect few details, these determined contributors are the optimum ways to understand a nation's climate actions [1].

The conscience that all living or not things that take place in nature are vital to preserving the world as a pleasant place materialises in the notion of environment. Although environmental regulations are considered the key component for mitigating global warming drifts and reforming carbon reduction, these policies are not uniformly implemented. Moreover, their assessments are limited to a global panel of countries. However, the Organization for Economic Cooperation and Development (OECD) guideline aims at enhancing environmental quality by devising stringent policies for climate change awareness. These policies include promoting green innovation and emissions regulations through carbon pricing in which environmental taxes are among the most significant regulations [2]. These guidelines have also brought innovation to the centre of climate change policy conversations to find the optimum solution for balancing economic growth and environmental quality.

As technology and innovation emerged as pivotal factors in efficient energy utilization, mitigating environmental degradation and achieving sustainable development, most studies (e.g., [3–16]) counted technology and innovation as determining parameters in modelling energy use and carbon emissions. However, their investigation focus was not on the technology itself. Nevertheless, patents as an indicator of innovation can significantly reduce greenhouse gases as they improve the technology through higher energy consumption and production efficiency, whose impacts have been less researched.

This research aims to investigate the performance of CO_2 gas emissions in relation to its significant determinants, namely gross domestic production (GDP), fossil fuels consumption, industrialisation, environmental tax revenue as a share of GDP/total taxation, environmental patents, and urbanisation, using the ordinary least squares (OLS) model estimator, and the modelling approach quantile regression for OECD countries. Our comprehensive analysis aims to draw interest in understanding how each parameter can be merged in different ways to address CO_2 gas emissions in OECD countries. Furthermore, to capture the influence of government regulations on reducing CO_2 gas emissions, the capacity of environmental taxation was examined as a fraction of the total tax burden and the overall tax burden to GDP.

Our study is not only contributing to the understanding of the drivers of CO_2 gas emissions by providing statistical measures. It is also novel in that it offers policymakers in OECD countries some valuable insights for designing policies, considering the effect of the measured parameters on CO_2 gas emissions. The empirical investigation is structured into six sections: Section 2 provides an important literature examination, and Sections 3 and 4 present the data, methodology, and estimation results. Section 5 provides the discussion. Finally, Section 6 presents the conclusions and policy implications.

2. Literature Review

This part will show the literature relevant to the empirical analysis. First, the relationship between environmental policies and greenhouse gas emissions was reviewed, considering environmental tax revenues as an indicator to measure the impact of government regulations. This analysis is followed by a review of the relationship between phenomena innovation through environmental patents and CO_2 gas emissions.

2.1. The Relationship between Environmental Policies and CO_2 Gas Emissions

The study by Ahmed shows that stringent environmental policies enhanced green innovation in 20 OECD countries [17]. However, these regulations may cause short-term negative economic shocks. Albulescu et al. [2] explored the effect of environmental policy stringency on the air pollution problem (CO_2 emissions) in 32 countries from the OECD from 1990 to 2015, employing a panel data methodology. The researchers discovered that a rise in policy stringency negatively affects environmental degradation, and environmental stringency has a stronger impact in countries with lower levels of environmental degradation. Moreover, there is a need to change policy stringency measures to environmental degradation levels to improve their effectiveness [2].

He et al. [18] conducted an empirical study of OECD countries and China from 2004 to 2016 to answer if the environmental tax policy helps to reduce pollutant emissions. The results showed that overall environmental taxes facilitate reducing pollutant emissions in the selected cases.

The effect of industrial structure and environmental regulations on carbon dioxide emission in 30 provinces in China was studied by Chen et al. [19], who observed that industrial restructuring could help to reduce carbon dioxide emissions. However, if the maximization level of the industrial structure is observed at a lower scale, environmental regulation stimulates carbon dioxide emission, and if it is high, environmental regulation significantly restricts carbon dioxide emission. Thus, policies related to environmental regulation adequate for indigenous conditions should be formulated based on the evolution of specific native industrial structures [19].

Neves et al. [20] investigated whether environmental regulation reduces environmental pollution, such as CO_2 gas emissions, in European Union countries between 1995 and 2017. Their findings showed that environmental regulation effectively reduces CO_2 gas emissions in the long term. In addition, policies that support renewable energy sources reduce CO_2 gas emissions in the short and long term. The effectiveness of these policies is further endorsed by a decrease in carbon dioxide emissions linked to foreign direct investment, indicating that the EU has effectively attracted innovative and high-quality investments [20].

In the same vein, Wang and Zhang [21] examined the effects of environmental regulations on CO_2 gas emission by considering 282 cities in China. The authors discovered an inverted U-shaped relationship, showing the direct impact of environmental regulations on CO_2 gas emission. This finding implies that environmental regulations can effectively moderate CO_2 gas emissions through technological innovation and restructuring of industrial structure. However, foreign direct investment indicates a pollution paradise effect within the constraints of environmental regulations [21]. Finally, Eskander and Fankhauser [22], in their study of 133 countries between 1999 and 2016, found both long- and short-term effects of environmental regulation on reducing carbon dioxide emissions.

Baloch et al. [23] analysed the role of governance in mitigating CO_2 emissions for Brazil, Russia, India, China and South African countries (BRICS) from 1996 to 2017. The results indicated that governance has a negative and significant effect on CO_2 emissions, helps to shape the Environmental Kuznets Curve hypothesis, and reduces CO_2 gas emissions in BRICS countries.

2.2. The Relationship between Innovation and CO_2 Gas Emissions

Koçak and Ulucak [24] investigated the impact of energy consumption and R&D development spending on reducing CO_2 gas emissions in OECD countries. Based on their findings, R&D spending on energy efficiency and fossil energy has an increasing effect on CO_2 gas emissions; however, no significant relationship was found between R&D spending on renewable energy and CO_2 gas emissions. Therefore, the study suggests strong evidence that R&D spending on energy and storage reduces CO_2 gas emissions.

Petrović and Lobanov [25], working on the effect of research and development expenditure on CO_2 gas emissions between 1981 and 2014 in 16 OECD countries, show a negative effect of R&D expenditure on CO_2 gas emissions, i.e., high R&D expenditure on average reduces CO_2 gas emissions. However, this hypothesis is not effective in 40% of countries. The results suggest that the average expected effect of R&D investments on CO_2 gas emissions should not be considered adverse until it is empirically estimated, as stated by different studies.

When considering OECD countries, Cheng et al. [26] investigated the direct and moderating effects of technological innovation, measured by the development of patents, on CO_2 gas emissions. The results show that technological innovation is directly responsible for reducing CO_2 gas emissions. However, this effect is considerably asymmetric and heterogeneous at different quantiles. Furthermore, technological innovations affect CO_2 emissions by increasing the negative impacts of renewable energy sources.

Similarly, Alam et al. [27], in their research, also considered OECD countries to investigate the impacts of the stock market and R&D investment on CO_2 gas emissions and green energy consumption. The authors found that the stock market and R&D investment have a significant long-run equilibrium relationship with CO_2 gas emissions and clean energy. Moreover, the long-run elasticities show a significant positive impact of stock market growth and R&D on clean energy consumption and a negative effect on CO_2 gas emissions.

Ahmad et al. [28] studied the impacts of innovation shocks in determining CO_2 emission levels in OECD economies. The results support that positive innovation shocks improve environmental quality, but negative shocks disrupt it.

Hashmi and Alam [29] focused on the dynamic relationships between innovation, environmental regulation, CO_2 gas emissions, economic growth and population in OECD countries, covering the years 1999 to 2014, and showed that an increase in environmentally friendly patents decreases carbon gas emissions, while an increase in environmental revenues per capita reduces carbon gas emissions in OECD nation-states.

Chen and Lee [30] explored the effect of technological innovation, particularly on reducing CO_2 gas emissions, in 96 countries from 1996 to 2018. Their study found that both CO_2 gas emissions and R&D intensity showed a significant spatial correlation within these countries. Furthermore, technological innovation does not significantly affect CO_2 gas emissions worldwide. However, cluster-based studies have reported that technological innovation in nations with high technology, high output, and high CO_2 gas emissions could significantly decrease CO_2 gas emissions in adjacent countries.

Cheng et al. [31] aimed to disclose the impacts of environmental patents and renewable energy on CO_2 gas emissions considering BRICS economies from 2000 to 2013. The study showed that renewable energy decreases CO_2 gas emissions per capita, the progress of environmental patents accelerates carbon dioxide emissions per capita, and GDP per capita increases CO_2 gas emissions per capita. Meirun et al. [32] studied the effects of green technology innovation on economic development and CO_2 gas emissions in Singapore, considering the period from 1990 to 2018, and found a positive and significant relationship with long-term and short-term carbon dioxide emissions.

Khattak et al. [33] explored the effect of technology innovation, green energy use, and income on environmental degradation in BRICS economies (e.g., China, India, Russia, South Africa, and Brazil). Their results indicated that innovation activities did not disrupt CO_2 gas emissions in all countries except Brazil. However, the authors also showed that green energy consumption had mitigated environmental degradation (CO_2 gas emissions) in BRICS. Furthermore, they found a bidirectional causal relationship between CO_2 gas emissions and technological innovation.

The study on the effect of R&D development expenditure on air pollution (CO_2 gas emissions) conducted by Fernández et al. [34], which included the European Union, the United States, and China, between 1990 and 2013, showed that R&D expenditure contributed positively to the reduction of CO_2 gas emissions of developed countries. The European Union is where the effect of this variable is lowest, followed by the United States, where energy consumption pollutes the most. The results obtained for China are different due to its economic and environmental performance. Du et al. [35] tried to determine whether technological innovations fostered a decrease in CO_2 emissions in 71 economies between 1996 and 2016. Their findings showed that green technology innovations are only effective in economies with a high-income level, and innovations do not significantly reduce CO_2 emissions for economies with income levels below the threshold.

Dauda et al. [36] investigated the relationship between innovation, trade liberalisation, and environmental degradation (CO_2 emissions) in selected African nations and found an inverted U-shaped relationship between environmental degradation and innovation. However, they observed that renewable energy use has less environmental degradation at the panel level.

Ganda [37] explored the impact of innovation and technology investments on environmental degradation (carbon emissions) in selected OECD economies. The authors found that consumption and spending on green energy research and development are negatively correlated with environmental degradation (carbon emissions). The research suggested that innovation and technology investments in these countries affect emissions differently and still have the potential to reduce environmental quality. They stressed that patents, including specifications of natural environmental standards and researchers empowered with ecological skills and knowledge, would facilitate the achievement of zero emissions targets.

Hasanov et al. [38] showed that technological progress and green energy consumption mitigate the CO_2 emissions in BRICS countries in the short run. However, the gross domestic product and import size increased pollution in the long and short term. Therefore, they recommended implementing measures and regulations and establishing legislative frameworks that promote technological advances and transition to sustainable energy.

Wang and Zhu [39] investigated whether energy technology innovations contribute to reducing CO_2 gas emissions in China. The results indicated that technological innovation in renewable energy technologies facilitates the reduction of CO_2 gas emissions, while fossil energy technology innovation is ineffective in reducing carbon emissions. Moreover, economic growth can agglomerate carbon emissions from low-growth provinces to neighbouring high-growth provinces; mandatory environmental regulation in China would shift carbon emissions from provinces with strict regulations to neighbouring provinces with lax regulations.

Abid et al. [40] investigated the effect of technological development innovation, financial development, and FDI on environmental degradation in G8 countries from 1990 to 2019. The authors found that these countries showed a statistically significant long-term and negative relationship between CO_2 and foreign direct investment, financial development, and technological innovation. Furthermore, a long-run bidirectional causality was found between economic growth, financial development, urbanization, trade openness, CO_2 gas emissions, and energy consumption; however, a unidirectional causality exists between CO_2 gas emissions and foreign direct investment.

Cheng et al. [41] investigated the impact of green energy and innovation on environmental degradation (CO_2 emissions) in OECD countries. Their findings provided comprehensive, important information on the relationship between carbon emissions per capita and different variables. More specifically, their impact on carbon emissions per capita is significant and positive for economic growth but decreases for fast-growing emissions countries. The results do not support the Environmental Kuznets Curve hypothesis. On the contrary, their impacts on carbon emissions showed an inverted U-shaped trend for renewable energy at different quantile levels.

3. Data and Methodology

The data and method used to carry out this empirical investigation will be shown in this section.

3.1. Data

This study uses data from 36 Organisation for Economic Co-operation and Development (OECD) countries from 1994 to 2015. This large sample allows a comprehensive analysis of CO_2 emissions performance through the perspective of GDP, fossil fuel consumption, industrialisation, environmental tax revenues as a share of GDP/total taxes, environmental patents, and urbanisation, using the fixed effects estimator and quantile regression modelling approach for a group of rich countries. Data are only available up to 2015, and the period is appropriate for analysing the effect of selected variables and observing the main flows in terms of environmental regulations and policies in OECD countries. To our knowledge, this period and 36 OECD countries have not been investigated in the existing literature. A list of countries (full sample, group 1, and group 2) is presented in the Appendix A section.

Although the relationships between CO_2 gas emissions against its determinants, including GDP, urbanisation, fossil fuel energy consumption, industrialisation, patents on environmental technologies, and environmental tax revenue, are widely discussed, the outcome is mixed [2,20,24,25]. Mostly the studies are criticized regarding their validity of the expected coefficients, and the econometric approaches applied are not appropriate for quantitative analysis, which is important to get unbiased and reliable regression outcomes. Hence, keeping in view the selected period and the effect of the causalities, the variable GDP and energy consumption are selected by following the studies [42,43]. The variable industrialisation is selected by following the studies [43–49]; environmental tax (% of GDP) is selected by following the studies [50,51]; the variable urbanisation is selected by following the studies [52–55]; the variable patents on environment technologies is selected by following the studies [24,26,30,33,34]. Finally, the variable environmental tax revenue (% of Taxation) is selected by following the studies [2,18,20,21,23]. Table 1 below summarises the variables, their definition, and the sources.

Table 1. Variable Definitions and Data Sources.

Variable	Definition	Sources
CO_2	Carbon dioxide emissions (metric tons per capita)	World Bank
GDP	GDP per capita (constant 2015 US$)	World Bank
Urb	Urban population (% of the total population)	World Bank
Fossil	Fossil Fuel Energy Consumption (% of Total)	World Bank
Indust	Industry (including construction), value added (% of GDP)	World Bank
Patents	Patents on Environment Technologies (% of Total Patents)	OECD Database
TaxToGDP	Environmental Tax Revenue (% of GDP)	OECD Database
TaxPerc	Environmental Tax Revenue (% of Taxation)	OECD Database

Table 1 above evidence the definitions and data sources of the variables used in this study, which models CO_2 emissions against their determinants, including GDP, urbanisation, non-renewable energy consumption, industrialisation, patents on environmental technologies, and environmental tax revenues. While environmental patents measure the impact of environmental innovations on CO_2 emissions, variable environmental tax revenues measure the impact of government policies and regulations, considering environmental taxation as a fraction of the total tax burden and the overall tax burden and as a percentage of GDP. In addition, the descriptive statistics of the variables used in this empirical investigation are shown in Table 2 below.

Table 2. Variables' Descriptive Statistics.

Main Variables	Observations	Mean	Standard Deviation	Minimum	Maximum
LnCO_2	792	2.038	0.526	0.292	3.292
LnGDP	783	10.141	0.743	8.271	11.566
LnUrb	792	4.313	0.153	3.920	4.583
LnFossil	789	4.243	0.373	2.327	4.590
LnIndust	771	3.229	0.209	2.344	3.716
LnPatents	777	2.162	0.484	−0.083	3.452
LnTaxToGDP	788	0.810	0.424	−3.912	1.680
LnTaxPerc	787	1.933	0.357	−2.407	2.942

Notes: (Ln) denotes variables in the natural logarithms; the command *sum* of Stata 17.0 was used in this empirical investigation.

3.2. Methodology

The main model estimation used in this study will be shown in this subsection. First, we describe a set of initial tests essential to characterise the data and assess which estimation method is the most appropriate. Then, this section shows the estimation that will be used to identify the effect of independent variables on CO_2 gas emissions. The fixed effects estimator encompasses different intercepts for the various countries to control for country-specific unobservable effects that are not captured by the covariates. In contrast to the fixed effects estimator, the panel quantile regression procedure developed by Canay [56] allows the identification of the effect of the independent variables (explanatory variables) on different parts of the conditional distribution of CO_2 gas emissions. Finally, we deal with the potential parameter heterogeneity among countries by forming groups using the method proposed by Lin and Ng [57]. Parameter heterogeneity is a common feature of panel data and can lead to biased estimates. This method clusters countries into data-driven groups, thus avoiding biased estimates and retaining the benefits of panel data estimation.

Indeed, in order to identify the characteristics of all variables used in this empirical investigation, the following preliminary tests will be performed:

(I) Shapiro–Wilk test for normality [58]. This test, which relies on order statistics, stipulates that. Indeed, the null hypothesis of this test is that the variables are normally distributed in the panel data;

(II) The variable inflation factor (VIF) assesses the severity of multicollinearity between the variables in the econometric model. Indeed, high multicollinearity between the model variables makes unstable parameter estimates;

(III) Cross-sectional dependence (CSD) test [59]. This test checks the presence of CSD between the variables in the panel data. According to the null hypothesis, different units are uncorrelated;

(IV) Panel unit root test (CIPS). This test aims to verify the stationarity among the variables in the model [60]. The null hypothesis of this test indicated that the series is non-stationary;

(V) Cointegration test [61]. This test checks for cointegration between the variables in the panel data. The null hypothesis of this test is that variables are not cointegrated;

(VI) The Hausman test [62]. This test identifies fixed effects (FE) or random effects (RE) estimates in the econometric models. The null hypothesis of this test is that the RE estimator is consistent and more efficient than FE.

After conducting the preliminary tests, we proceed to the estimation stage. We use panel quantile regression as the primary method. Quantile regression has several advantages over traditional least squares methods. First, unlike least squares methods that rely on the conditional mean, it provides a complete picture of covariates' impact on the dependent variable's entire distribution. Second, it is robust in the presence of outliers, which generate large shifts in the least squares estimates. Finally, it does not require normally distributed data.

We model the relationship between the logarithm of per capita CO_2 gas emissions and the explanatory variables through the following equation:

$$ln_{CO2i,t} = \alpha_i + X'_{i,t}\beta(U_{i,t}) \tag{1}$$

where the $i = 1, 2, \ldots, 36$ identifies the country, $t = 1994,\ 1995, \ldots,\ 2015$ is the observation year, α_i is the country-specific fixed effect, $X'_{i,t}$ is the explanatory variables' vector, which includes a constant, $ln_{GDPi,t}$, $ln_{Urbi,t}$, $ln_{Fossili,t}$, $ln_{Industi,t}$, $ln_{Patentsi,t}$, $ln_{TaxToGDPi,t}$, and $ln_{TaxPerci,t}$, $\beta(U_{i,t}) = (\beta_0, \beta_1, \ldots, \beta_7)$ is the corresponding coefficients vector, and $U_{i,t}$ is a uniformly distributed random variable on the interval $[0,\ 1]$.

It is well known that when the unobserved fixed effects are correlated with the covariates, the simple quantile regression estimates become inconsistent. Canay [56] proposes a two-stage estimation procedure that avoids this problem when the FE is a pure location shift, and $U_{i,t}$ and α_i are independent. Let $u_{i,t} \equiv X'_{i,t}\left[\beta(U_{i,t}) - \beta_\mu\right]$, where β_μ represents the conditional mean of $\beta(U_{i,t})$. Then, from Equation (1), we get

$$ln_{CO2i,t} = \alpha_i + X'_{i,t}\beta_\mu + u_{i,t} \tag{2}$$

Canay's two-stage procedure for the estimation of quantile τ's parameters develops as follows:

(1) Derive a consistent estimate of β_μ, using Equation (2), and let $\hat{\alpha}_i \equiv T^{-1}\sum_{t=1}^{T}\left[ln_{CO2i,t} - X'_{i,t}\hat{\beta}_\mu\right]$, where $\hat{\beta}_\mu$ is the estimate of β_μ;

(2) Estimate the explanatory variables' coefficients by solving the following problem

$$\hat{\beta}(\tau) \equiv argmin_\beta \frac{1}{T \times N}\sum_{t=1}^{T}\sum_{i=1}^{N}\left[\rho_\tau\left(ln\hat{_{CO2i,t}} - X'_{i,t}\beta\right)\right] \tag{3}$$

where $\hat{ln_{CO2i,t}} = ln_{CO2i,t} - \hat{\alpha}_i$, ρ_τ is the check function for quantile τ, N, and T are the number of countries and years in our sample, respectively. Canay [56] demonstrates that the estimates obtained through this procedure are consistent and asymptotically normal. In our implementation, we use the fixed effects estimates in the first stage and compute the bootstrap standard errors for the final estimates using 1000 replications. Finally, we benchmark the quantile regression results against the traditional fixed effects estimates.

Standard panel data models often implicitly assume the effect of the covariates on the dependent variable is the same for different cross-sectional units. However, there is no aprioristic reason to believe the slope coefficients must be equal. Thus, to test the robustness of our results, we resort to the panel data model with group-specific parameters proposed by [57]. These authors assume the slope coefficients are the same within a group of countries but may differ from one group to another. They take an utterly agnostic view about the number of groups in the panel and their composition and propose a modified K-means algorithm to achieve conditional clustering. To implement this algorithm, we first need to choose the number of groups, G, and randomly assign the countries to one of the groups. Then, the following two-step procedure is repeated until convergence:

(1) Estimate the fixed effects slope coefficients, β_g, separately for each group;
(2) Reassign country i to group g', where g' is the solution to the following problem

$$g' = argmin_g \sum_{t=1}^{T} \left[\dddot{ln}_{CO2i,t} - \dddot{X}'_{i,t}\beta_g \right]^2 \quad (4)$$

where $\dddot{ln}_{CO2i,t}$ and $\dddot{X}'_{i,t}$ are the demeaned dependent variable and covariates for country i at time t. Therefore, step 2 must be done for every country in the sample.

Lin and Ng argue that the estimates are sensitive to the initial group allocation [57]. Thus, we repeat this algorithm one million times for each choice of G.

The final step in Lin and Ng's method is choosing the optimal number of groups. They propose choosing the value of G that minimizes the following modified BIC criterion:

$$BIC\left(\tilde{G}\right) = ln\left[\frac{1}{NT}\sum_{g=1}^{\tilde{G}}\sum_{i\in I_g}\sum_{t=1}^{T}\left[\dddot{ln}_{CO2i,t} - \dddot{X}'_{i,t}\hat{\beta}_g\right]^2\right] + \tilde{G}K\frac{c_{NT}ln(NT)}{NT} + \left(\tilde{G}-1\right)\frac{ln\left(N^2\right)}{N^2} \quad (5)$$

where K denotes the number of regressors, $c_{NT} = \sqrt{min(N,T)}$, and $\hat{\beta}_g$ is the vector of estimates for group g.

Given the reduced number of cross-sectional units in our sample, we consider the possibility that there are, at most, three different groups. First, we run the algorithm described above 1 million times for $G = 2$ and choose the group composition that minimizes the modified *BIC* criterion. Then, we do the same for $G = 3$. Finally, we compare the *BIC* criterion values for the estimation with one group (just the standard fixed effects estimator), two groups, and three groups and select the number of groups with the lowest *BIC*.

4. Empirical Analysis

This section presents the results of the preliminary tests. Estimates of the effect of covariates on CO_2 gas emissions for the full sample and the different groups are also presented. In addition, we chose to analyse the impact of the explanatory variables at the 10th, 25th, 50th, 75th, and 90th quantiles of the dependent variable to get a complete picture of their influence on the different zones of the distribution of CO_2 gas emissions. Table 3 below reveals that the null hypothesis of a normal distribution is strongly rejected for the dependent and the independent variables. However, we should note that this lends more weight to our choice of resorting to quantile regression, as this method does not require normally distributed data.

The inflation variation factors (VIF) show that multicollinearity does not affect our model. However, all FIV are well below the commonly accepted threshold of 10, and the average VIF is below the reference value of 6 (see Table 4 below).

Table 3. Normality test (Shapiro–Wilk test).

Main Variables	Obs.	W	V	Z	Prob > z
$LnCO_2$	792	0.961	19.883	7.333	0.0000
LnGDP	783	0.952	24.481	7.839	0.0000
LnUrb	792	0.959	20.735	7.436	0.0000
LnFossil	789	0.730	137.430	12.072	0.0000
LnIndust	771	0.966	16.961	6.935	0.0000
LnPatents	777	0.961	19.425	7.270	0.0000
LnTaxToGDP	788	0.848	77.243	10.659	0.0000
LnTaxPerc	787	0.875	63.345	10.172	0.0000

Notes: The command *swilk* of Stata 17.0 was used in this empirical investigation.

Table 4. VIF-test.

Main Variables	VIF	1/VIF	Mean VIF
LnGDP	3.58	0.279	
LnUrb	3.45	0.290	
LnFossil	1.68	0.596	
LnIndust	1.40	0.716	1.93
LnPatents	1.27	0.787	
LnTaxToGDP	1.09	0.915	
LnTaxPerc	1.05	0.949	

Notes: The command *vif* of Stata 17.0 was used in this empirical investigation.

Indeed, Table 5 below shows the results of the Pesaran cross-sectional dependence test [59]. The absence of cross-sectional dependence is strongly rejected for all variables, suggesting that common shocks drive their evolution across countries. This phenomenon implies that standard errors in the traditional fixed-effects estimates are biased. To deal with it, we use the Driscoll and Kray [63] standard errors in the fixed effects estimates and bootstrapped standard errors in the panel quantile regressions.

Table 5. CSD-test.

Main Variables	CD-Test	*p*-Value	Corr	Abs (Corr)
$LnCO_2$	29.63	0.000	0.253	0.535
LnGDP	101.98	0.000	0.879	0.879
LnUrb	39.66	0.000	0.339	0.858
LnFossil	39.96	0.000	0.343	0.612
LnIndust	45.68	0.000	0.404	0.550
LnPatents	52.55	0.000	0.461	0.479
LnTaxToGDP	12.70	0.000	0.112	0.465
LnTaxPerc	12.80	0.000	0.113	0.450

Notes: The command *xtcd* of Stata 17.0 was used in this empirical investigation.

Next, we test all variables for stationarity. Again, we resort to the CSD test [60] since it is robust in the presence of CSD. Table 6 below reveals that all variables are nonstationary in the specification without trend, except for LnPatents. When a trend is included, both $LnCO_2$ and LnPatents are stationary, while the remaining variables are not.

When variables are nonstationary, we have to check whether they are cointegrated. Otherwise, we could incur the problem of spurious regression. However, all variants of the Pedroni cointegration test [61] strongly reject the null hypothesis of no cointegration. Therefore, as shown in Table 7 below, we need not worry about the spurious regression problem.

Finally, the Hausman test (see Table 8 below) slightly rejects the hypothesis that the RE estimator is consistent. Therefore, this investigation chooses to apply the FE estimator because of its consistency, although it may be inefficient when the null hypothesis holds. The alternative of choosing the random effects estimator may result in biased estimates, which is a more serious problem.

Table 6. CIPS-test.

Main Variables	CIPS-Test (Zt-Bar)		
	Lags	Without Trend	With Trend
		Zt-Bar	Zt-Bar
$LnCO_2$	1	0.766	−1.861 **
LnGDP	1	0.217	1.599
LnUrb	1	0.094	2.994
LnFossil	1	−0.813	0.128
LnIndust	1	−0.915	2.171
LnPatents	1	−4.898 ***	−5.159 ***
LnTaxToGDP	1	1.172	2.943
LnTaxPerc	1	1.376	4.513

Notes: The command *multipurt* of Stata 17.0 was used in this empirical investigation; *** and ** indicate a statistically significant at the (1%) and (5%) levels, respectively.

Table 7. Pedroni cointegration test.

Estimator	Statistic	*p*-Value
Modified Phillips–Perron test (MPP)	5.485	0.000
Phillips–Perron test (PP)	−8.909	0.000
Augmented Dickey–Fuller test (ADF)	−10.159	0.000

Notes: The command *xtcointtest* of Stata 17.0 was used in this empirical investigation.

Table 8. Hausman test.

Test Distribution	Statistic	*p*-Value
Chi-squared (7)	13.22	0.0670

Notes: The command *hausman* of Stata 17.0 was used in this empirical investigation.

Next, we report the estimates for the full sample. Table 9 below reveals the estimates of panel quantile regression and ordinary least squares (OLS) regression.

Table 9. Estimations for $LnCO_2$.

Independent Variables	Quantiles (Q)					OLS Model
	10Q	25Q	50Q	75Q	90Q	FE Estimator
LnGDP	0.2511 ***	0.2327 ***	0.2417 ***	0.2226 ***	0.2046 ***	0.2327 ***
LnUrb	−0.3777 **	−0.3585 **	−0.3585 **	−0.3337 **	−0.3564 **	−0.3557 ***
LnFossil	0.5507 ***	0.5560 ***	0.5056 ***	0.4567 ***	0.4252 ***	0.4820 ***
LnIndust	0.4025 ***	0.3569 ***	0.3392 ***	0.3165 ***	0.3088 ***	0.3405 ***
LnPatents	−0.0567 ***	−0.0629 ***	−0.0571 ***	−0.0322 **	−0.0115	−0.0381 ***
LnTaxToGDP	0.2796 ***	0.2996 ***	0.2498 ***	0.2080 ***	0.2335 ***	0.2450 ***
LnTaxPerc	−0.2484 ***	−0.2746 ***	−0.2035 ***	−0.1449 ***	−0.1637 ***	−0.1967 ***
Constant	−2.2499 **	−1.9219 **	−1.7975 **	−1.5060 *	−1.0466	−1.6726 ***

Notes: The commands *stscc*, *xtreg*, and *qreg* of Stata 17.0 were used in this empirical investigation. ***, **, and * denote statistical significance at the (1%), (5%), and (10%) levels, respectively.

Table 9 above reveals that the FE model results show a positive dependence of CO_2 gas emissions on GDP. However, the elasticity is lower than one, which means the carbon intensity of economies decreases as they grow. The quantile regression estimates show the detrimental impact of economic development on air pollution (CO_2 emissions), which is felt more noticeably in the lowest quantiles. Additionally, the effects of fossil fuel consumption, industrialisation, and the tax burden as a fraction of GDP on CO_2 gas emissions are akin to GDP—they cause an increase in emissions that predominantly affect the lowest quantiles. On the contrary, environmental taxation as a fraction of the total tax burden and the number of environmentally related patents contribute to reducing emissions. Urbanisation also mitigates CO_2 gas emissions, and its influence is broadly stable across quantiles. Indeed, Figure 1 below summarises the results found in Table 9 above.

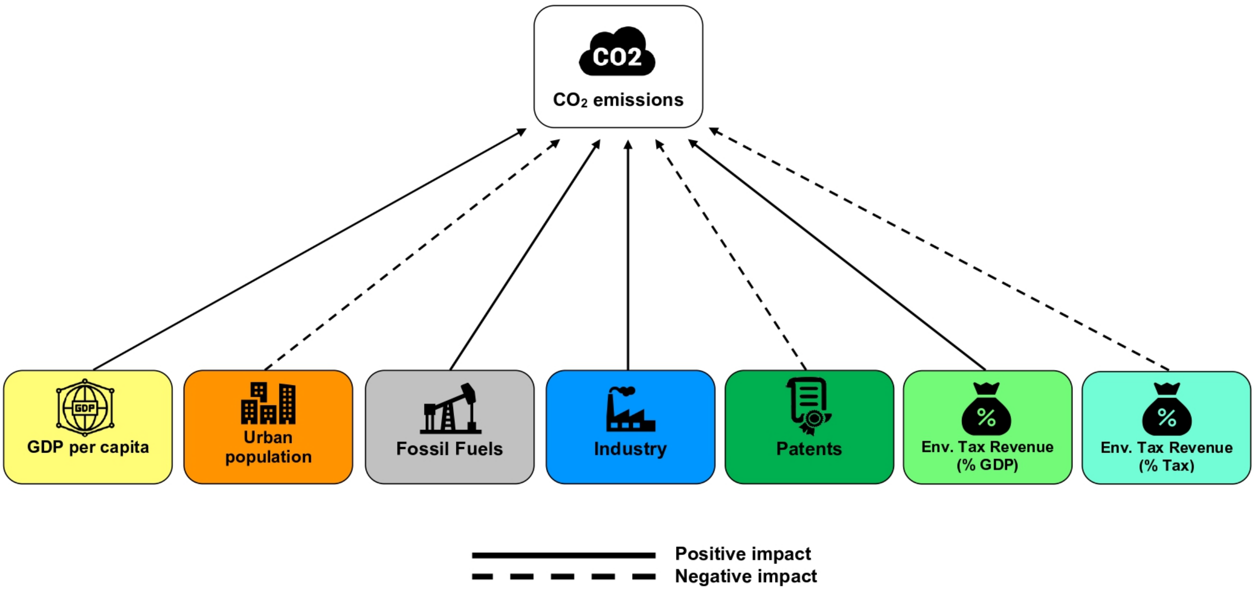

Figure 1. The impact of independent variables on the dependent. This figure was based on the results in Table 9 above. The authors conceived this figure.

Finally, we present the estimates for the different groups. According to the modified BIC criterion, two groups are optimal. Therefore, Table 10 below shows the estimations for $LnCO_2$ for the two groups.

Table 10. Estimations for $LnCO_2$ for the two groups.

Independent Variables		Quantiles (Q)					OLS Model
		10Q	25Q	50Q	75Q	90Q	FE Estimator
LnGDP	G1	0.0975 **	0.0873 **	0.0888 **	0.0858 **	0.0835 **	0.0881 *
	G2	0.5856 ***	0.6046 ***	0.6059 ***	0.6044 ***	0.5972 ***	0.5988 ***
LnUrb	G1	−2.3890 ***	−2.4168 ***	−2.4534 ***	−2.5096 ***	−2.5230 ***	−2.4557 ***
	G2	−0.6917 ***	−0.6912 ***	−0.7040 ***	−0.6902 ***	−0.6515 ***	−0.6799 ***
LnFossil	G1	0.2833 ***	0.2855 ***	0.2681 ***	0.2336 ***	0.2121 ***	0.2508 ***
	G2	1.6721 ***	1.6928 ***	1.7371 ***	1.7308 ***	1.7554 ***	1.7199 ***
LnIndust	G1	0.4518 ***	0.4197 ***	0.4285 ***	0.3926 ***	0.4147 ***	0.4270 ***
	G2	0.0808 *	0.0978 **	0.1328 ***	0.1383 ***	0.1155 **	0.1236 ***
LnPatents	G1	−0.0333 *	−0.0305 *	−0.206	−0.0122	0.0044	−0.0121
	G2	−0.0196	−0.0254 **	−0.0101	−0.0028	−0.0045	−0.106
LnTaxToGDP	G1	0.5132 ***	0.5504 ***	0.5367 ***	0.5434 ***	0.5461 ***	0.5299 ***
	G2	0.0398	0.0150	0.0180	0.0100	0.0205	0.0274
LnTaxPerc	G1	−0.5404 ***	−0.5727 ***	−0.5767 ***	−0.5805 ***	−0.5772 ***	−0.5540 ***
	G2	0.0120	0.0303	0.0003	0.0183	−0.0014	0.0055
Constant	G1	9.3067 ***	9.7027 ***	9.9305 ***	10.491 ***	10.590 ***	9.9667 ***
	G2	−8.5375 ***	−8.8487 ***	−9.0539 ***	−9.1077 ***	−9.1736 ***	−9.0108 ***

Notes: The commands *stscc*, *xtreg*, and *qreg* of Stata 17.0 were used in this empirical investigation.G1 and G2 represent group 1 and group 2, respectively. ***, **, and * denote statistical significance at the (1%), (5%), and (10%) levels, respectively.

Table 10 above shows that the signs of the estimated coefficients agree almost perfectly with those of the full sample. However, there are some relevant differences. First, the mitigating effect of patents is only noticeable at the 10th and 25th quantile for group 1 and at the 25th quantile for group 2. Second, environmental taxation does not influence group 2 countries. Finally, comparing groups 1 and 2, we can observe that GDP and fossil fuel consumption have a more significant detrimental impact on the latter than on the former. On the contrary, industrialisation mainly increases emissions from group 1 countries. However, interestingly, the decrease in CO_2 emissions caused by urbanisation is larger for both groups than in the full sample, particularly for group 1.

5. Discussion

This section will present the possible discussions for the results found in this empirical investigation. Therefore, the variables LnGDP, LnFossil, LnIndust, and LnTaxToGDP positively affect the variable $LnCO_2$, i.e., they increase CO_2 gas emissions. In contrast, the variables LnUrb, LnPatents, and LnTaxPerc have a negative impact on the variable $LnCO_2$, i.e., they mitigate environmental degradation (CO_2 gas emissions). In light of these results, this empirical research raised a question: What are the probable explanations for the results? In the literature, the positive effect of the LnGDP variable on the $LnCO_2$ variable has been found by several authors (e.g., [26,31,41–44]).

For example, Fuinhas et al. [42] investigated the effect of electric vehicles, GDP, and consumption of energy on (GHG) greenhouse gas emissions in 29 countries from the European Union (EU) between 2010 and 2020. The empirical results from their analysis indicated that GDP exerts a positive impact on GHGs. In fact, in consonance with the authors, this positive effect is related to EU countries depending on the consumption of fossil fuels energy sources to grow through the rapid energy transition process. This idea is shared by Mendonça et al. [43]. These authors, who studied the effect of economic growth, population, and green energy sources on environmental degradation (CO_2 gas emissions) in 50 countries over the period 1990–2015 found an increase of 1% in GDP generated 0.27% in environmental degradation (CO_2 gas emissions) in all the countries studied. However, the same authors also showed that most countries from the EU depend on energy from non-renewable energy sources to grow.

The positive effect of the LnFossil and LnIndust variables on $LnCO_2$ is related to the variable LnGDP. Economic growth influences industrialisation processes (and vice versa) and energy consumption. This view is shared by Fuinhas et al. [42] and Nawaz et al. [44] As Nawaz et al. [44] said, modern production techniques make industrial production more attractive and efficient in developing and advanced nations. Therefore, this industrialization process increases the use of non-green energy sources.

Moreover, the same authors complement that industrialisation substantially influences economic growth and enhances the quality of life by raising the supply of goods and services. On the other hand, efforts to increase the gross domestic product per capita through increased production have a negative effect on the ecosystem. Fuinhas et al. [42] complement that the positive effect of the independent variables LnFossil and LnIndust on the dependent variable $LnCO_2$ is related to the high use of polluting energy sources by households and industries. In European countries, in 1990 for example, 71.2% of final electricity consumption came from polluting energy sources, while green energy sources had a share of 4.34% in the energy mix in the EU. However, in 2019, there was a change in this scenario, where non-alternative energy sources had a share of 69.5% in the energy mix, while green energy sources had a share of 16%. Other authors also found the positive impact of independent variables LnFossil and LnIndust on dependent variable $LnCO_2$ (e.g., [43,45–49]).

The positive effect of the independent variable LnTaxToGDP on the dependent variable the $LnCO_2$ was found by Ren et al. [50], investigating the influence of environmental tax burden on the economy and society on air pollution (CO_2 gas emissions) in 21 countries from OECD during the period from 1991 to 2014. The authors found that moderate taxes could help to reduce air pollution emissions, but the effect of excessive taxation is the opposite. Therefore, another possible explanation for the positive impact of the independent variable LnTaxToGDP on the dependent variable LnCO_2 could be related to the inefficiency of the tax burden, as suggested by Fuinhas et al. [51].

Some authors also observed the adverse effect of the variable LnUrb on the variable LnCO_2 (e.g., [52–55,64–66]). According to Koengkan and Fuinhas [52], the negative effect of urbanization on environmental degradation (CO_2 gas emissions) may be related to two reasons. Firstly, it may be associated with the decrease in urban population impacting energy consumption by businesses, families, and the transport sector, consequently impacting environmental degradation (CO_2 gas emissions). According to Europa [67], in some countries of the European Union (EU), a decrease in urban population is projected, such as Portugal (−1.6%), Bulgaria (−1.4%), Hungary (−1.7%), Italy (−3.1%), Lithuania (−2.7%), Poland (−10.3%), Romania (−8.6%), Latvia (−17.7%), and Greece (−16.7%). However, over the same period, the entire rural population is expected to increase in only four EU countries, such as Sweden (+10.9%), Ireland (+24.5%), Belgium (+1.0%), and Denmark (+1.2%).

In contrast, almost 20 Member States are expected to have a fall in their entire rural population, ranging from (−43.5%) in Lithuania to (−0.6%) in Austria. In addition, substantial falls exceeding 20% are also expected for Latvia's rural population of almost (−37.6%), along with the rural populations of Romania (−25.0%), Croatia (−23.3%), and Bulgaria (−26.8%). Moreover, it could be related to (a) the improvement in energy efficiency caused by the introduction of new green energy technologies; (b) the diversification of energy sources, with the inclusion of green energy sources in the energy matrix in large urban centres; and (c) the introduction of environmental regulations, which encourage the acquisition of environmentally friendly technologies by industries and households and restrict the use of fossil fuel-powered cars, or other transport in urban centres, as occurs in some large cities in OECD countries. In addition, massive investment in public transport powered by alternative energy sources reduces the use of individual transport.

Several authors have found the negative impact of the LnPatents variable on LnCO_2 (e.g., [24–30,33–38,40]). The negative impact of the LnPatents variable has been related to the increase in patents on alternative/green energy technologies and technologies with high energy efficiency. For example, green industries are already booming in the EU. Therefore, the environmental industry sector in the EU grew by more than (50%) between 2000 and 2011. In this sector, more than 3 million people already work for eco-industries. Indeed, one-third of the global green technology market is supplied by European companies—a market worth €1 trillion today and expected to double in five years [68]. This increase will therefore reduce the consumption of fossil fuels energy sources and hence CO_2 gaseous emissions. Moreover, the negative impact of patents on environmental degradation (CO_2 gas emissions) indicates that OECD countries are investing massively in green technologies and eco-innovative initiatives to mitigate the impact of human activity on the environment.

Finally, several authors in the literature have found the negative effect of the independent variable LnTaxPerc on the dependent variable LnCO_2 (e.g., [2,17,18,20–23,26]). Thus, the ability of environmental taxation as a fraction of the total tax burden to reduce environmental degradation (CO_2 gas emissions) is due to the efficiency of environmental policies that reduce the consumption of non-renewable energy sources and, thus, CO_2 emissions. Another explanation is that environmental regulation promotes environmental degradation (CO_2 gas emissions) when the optimisation of industrial structures is low. However, when the optimisation of industrial structures is high, environmental regulation significantly inhibits carbon dioxide emissions [26].

6. Conclusions, Policy Implications and Limitations

This study provides a comprehensive analysis of CO_2 emissions performance through the perspective of GDP, fossil fuel consumption, industrialisation, environmental tax revenues as a percentage of GDP/total taxes, environmental patents, and urbanisation, using the fixed effects estimator and quantile regression modelling approach for OECD countries.

This study considered panel data from 36 OECD member countries from 1994 to 2015. Our empirical results indicated that GDP, fossil fuel consumption, industrialisation and GDP tax positively affect and, as a result, intensify CO_2 gas emissions. In contrast, urbanisation, environmental patents, and environmental tax as a percentage of total tax mitigate the CO_2 gas emissions in OECD countries. Furthermore, the study validates that industrialisation accelerates economic growth, thus showing that the positive impact of non-renewable energy consumption and industrialisation on CO_2 emissions is linked to GDP.

Similarly, the positive effect of the GDP tax on CO_2 emissions reflects that a moderate tax burden could help to reduce carbon emissions in member countries. However, the other variables used in the study, such as urbanisation, show a negative effect on CO_2 gas emissions, which could be mainly associated with the reduction of the urban population. This result will ultimately affect energy consumption, in particular, from industries, households, and the transport sector, plus the impact of introducing the latest energy technologies and renewable sources into larger urban clusters and the induction of environmental regulations in the OECD countries. Likewise, environmental patents negatively affect CO_2 gas emissions because of the high patents' investments in green technologies and eco-innovation initiatives. Finally, the negative effect of the environmental tax as a percentage of total taxes on CO_2 gas emissions reflects the efficient impact of environmental policies, which facilitate the reduction of energy consumption and, consequently, CO_2 gas emissions. These results confirm most of the previous findings present in the existing literature. However, the study found that environmental taxation does not influence group 2 countries (Appendix A) when dividing the sampled countries into two groups.

The findings of this study have important policy implications. The effect of industrialisation on environmental degradation is an observable fact. Once the country reaches the permissible thresholds, it is necessary to maximise energy consumption. The policymakers should design policies that help them to promote environmentally sustainable economic growth by imposing and accumulating environmental taxes. These environmental taxes, the discharge system, and the credit could endorse modifying industrial structures and economic growth modes. Policymakers should also resort to policies that foster trade of electric power produced by nuclear energy to neighbouring OECD countries. Using nuclear energy to produce electricity will ultimately affect the CO_2 gas emissions in the importing countries. Hence, carefully drafted environmental regulations are required in OECD countries to use energy efficiently.

The study has some limitations that may encourage further research. First, this study focuses only on the OECD nations considered developed countries. It would be valuable if a comprehensive analysis compared OECD countries with developing countries, such as ASEAN and South Asian countries enduring severe threats of CO_2 gas emissions. Future research can also deploy the latest analytical approaches with different periods and variables and offer forecasts for different country groups.

Author Contributions: All authors contributed to the study's conception and design. F.D. prepared material, collected data, and worked on the introduction and literature review. N.S. created the methodology and performed data analysis. M.K. wrote the discussion section. Conclusions, policy implications and limitations were written by N.N. J.A.F. reviewed, commented on and revised the manuscript. All authors commented on previous versions of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Country list: Australia, Austria, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States of America.

Group 1: Australia, Belgium, Canada, Colombia, Estonia, Germany, Hungary, Iceland, Ireland, Latvia, Lithuania, Norway, Poland, Slovak Republic, Sweden, the United Kingdom, and the United States of America.

Group 2: Austria, Chile, Czech Republic, Denmark, Finland, France, Greece, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Portugal, Slovenia, Spain, Switzerland, and Turkey.

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