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THE IMPACT OF ENVIRONMENTAL TECHNOLOGIES AND ENVIRONMENTAL POLICY STRINGENCY ON ENVIRONMENTAL DEGRADATION

Çevreyle İlgili Teknolojilerin ve Çevresel Politika Katılığının Çevresel Bozulmaya Etkisi

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JEL Kodları: O13, Q50, Q55, Q58.

Abstract

The increase in global warming and environmental pollution accelerates ecological degradation and prompts governments worldwide to adopt policies aimed at addressing environmental challenges while maintaining economic growth. In this context, this study examines how environmental technologies and policy stringency affect CO_2 emissions using panel data from 38 OECD countries for the period 1990-2022. The analysis, based on fixed effects and Driscoll-Kraay (1998) estimators, reveals that per capita GDP, exports, industrial activities, fossil fuel consumption, and education expenditures support economic expansion but also contribute to higher emission levels. The results indicate that both energy use and policy stringency significantly impact emission outcomes. While the proportion of environmental technologies reduces emissions, the unexpected positive relationship shown by the number of patents may be attributed to the time lag between the implementation of patents or to the production of more patents in high-emission countries. Overall, the findings indicate that environmental innovation alone cannot achieve emission reductions; it must be supported by strong policy implementation.

Anahtar Kelimeler: Çevresel Bozulma, Karbon Emisyonu, Çevre Teknolojisi Yenilikleri, Çevresel Politika Katılığı, Dinamik Panel Veri.

JEL Codes: O13, Q50, Q55, Q58.

Öz

Küresel ısınma ve çevre kirliliğinin artışı ekolojik bozulmayı hızlandırmakta ve dünya genelinde hükümetleri ekonomik büyümeyi korurken çevresel zorlukları ele almayı amaçlayan politikalara yöneltmektedir. Bu bağlamda, 1990-2022 dönemi 38 OECD ülkesine ait panel verileri kullanan bu çalışmada, çevre teknolojilerinin ve politika katılığının CO_2 emisyonlarını nasıl etkilediği araştırılmaktadır. Sabit etkiler ve Driscoll-Kraay (1998) tahmincilerine dayanan analiz, kişi başına düşen GSYİH'nin, ihracatın, endüstriyel faaliyetlerin, fosil yakıt tüketiminin ve eğitim harcamalarının ekonomik genişlemeyi desteklediğini ancak aynı zamanda daha yüksek emisyon seviyelerine de katkıda bulunduğunu ortaya koymaktadır. Çıkan sonuçlara göre hem enerji kullanımı hem de politika katılığı emisyon sonuçlarını önemli ölçüde etkilemektedir. Çevresel teknolojilerin oranı emisyonları azaltırken, patent sayısının gösterdiği beklenmedik pozitif yönlü ilişki, patentlerin ortaya çıkması ve uygulamaya geçmesi arasındaki gecikmeye veya yüksek emisyonlu ülkelerde daha fazla patent üretilmesine bağlanabilir. Genel olarak bulgular, sadece çevresel inovasyonun emisyon azaltımları sağlamak için yeterli olmadığını; güçlü politika uygulamaları ile desteklenmesi gerektiğini göstermektedir.

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1. Introduction

Sustainable development seeks to address the long-term well-being of society by harmonizing objectives of growth with breakthroughs that aim for development without any environmental deterioration (Ahmad et al., 2023). However, population growth, rapid urbanization, and structural transformations create pressures on the environmental system, throwing it out of natural balance. These pressures tend to release harmful pollutants and emissions into the system, and over time, lead to resource and habitat depletion (Yeganeh, 2020). Thus, the degradation of the environment threatens the system as well as human health, quality of life, and development (World Bank, 2016). The document by Tang et al. (2023) states that the predominant driver of climate change and global warming is the rise of CO_2 emissions, which constitute nearly 75% of the world's greenhouse gas emissions. The IPCC (2018) has even predicted that this could lead to significant environmental and socio-economic challenges in the near future.

Environmental technology or innovation is defined as the integration of scientifically based experts into societal decision-making processes aimed at preventing or reducing ecological degradation (Marx, 1992). These innovative ecosystems are groups of people, organizations, universities, government agencies, and institutions that develop the infrastructure to deliver and disseminate new developments and turn them into concrete practice. (Markard and Truffer, 2008). In addition to the advancement of techniques, eco-innovation also involves the organizational, societal, and cultural behavioral dimensions, and this is a multi-layered process of transformation (Rennings, 2000). In this context, the development and use of environmentally associated technologies and techniques that assist in the lowering of greenhouse gas emissions and ecological footprints are fundamental to the achievement of the objectives of sustainability (Wang et al., 2020a; Suki et al., 2022).

Energy efficiency technology reduces resource consumption in manufacturing processes (Samargandi, 2017). Patents in carbon-free energy domains demonstrate the potential for innovation (Wang et al., 2012). Peng et al. (2022) suggest that integrating technologically advanced knowledge, skills, and infrastructure leads to a multi-layered economic framework, enabling creative solutions. Information and communication technologies (ICTs) can be effective in reducing emissions through increasing productivity and industrial optimization purposes (Adebayo et al., 2022), and technology-focused indicators such as fixed-line and mobile phone usage are observed to be used in measuring their impact on CO_2 emissions (Su et al., 2021). Similarly, it applies to renewable electricity generation through wind, solar, and other biomass components, which reduce carbon emissions by reducing the use of fossil fuels (Bhatia, 2014; Bilgili et al., 2025). The field of environmental technologies also encompasses bioremediation, in which microorganisms are used to reduce pollutants (Das et al., 2023), artificial intelligence-based water management (WIPO, 2024), waste management, and eco-design (Sharma et al., 2024). In addition, the development of the digital economy, clean energy infrastructure, and energy-saving technologies promotes the spread of eco-innovations (Zhao et al., 2024); meanwhile, financial innovations and the quality of institutions also help reduce environmental degradation (Hussain and Dogan, 2021; Huo et al., 2023).

Policy created at the same time as technological advances helps to mitigate degradation. Modern policies try to integrate environmental damage into the cost of Pigou (1920) conceptualized environmental damage as a negative externality. As emphasized in Ajeigbe and

Ganda (2024), Many countries have imposed stricter environmental regulations in an effort to control degradation and to attain sustainability. As supported by Neves et al. (2020) and the OECD (2016), the reason for implementing strict environmental policies is to encourage both producers and consumers to make environmentally friendly choices by changing their behavior. These policies make environmentally harmful practices less attractive. In particular, the content and strictness of environmental policies implemented by governments have become an important factor in determining the direction of environmental degradation. The Environmental Policy Stringency (EPS) index was built for OECD member states, which allows them to measure and compare efforts made by different countries regarding the strictness of their environmental policies and the resulting necessary policy instruments in the area. Policy instruments were evaluated in the index as explained in the theoretical basis and methods of calculation by Botta and Koźluk (2014). In the first iteration, the index simply evaluated market-based policy instruments, which included carbon taxes, energy taxes, emissions trading systems, and market instruments like research and development (R&D) subsidies, feed-in tariffs, and renewable energy auctions. Subsequently, non-market instruments were included in the evaluation system, which included mandatory and voluntary standards and support and mixed technology instruments (Kruse et al., 2022). Each of the instruments is scored based on the stringency and is amalgamated in a composite measure, which serves the purpose of assessing and comparing countries and cross-temporal comparisons (Frohm et al., 2023).

The EPS index provides a comprehensive data structure and, in this capacity, allows for the empirical testing of theoretical approaches used to examine the relationship between economic growth, policy stringency, and environmental innovation, as well as those employed to explain environmental degradation. In the hypothesis proposed by Kuznets (2019) and subsequently developed, it is stated that environmental degradation will increase in the initial stages of economic growth and will decrease in later stages with the development of environmentally focused policies and technologies. In addition, Porter and van der Linde (1995) argued that well-designed environmental policies could facilitate the adoption of environmentally focused technologies and thereby help reduce environmental degradation. Within the framework of these hypotheses, two important variables emerge that serve to reduce environmental degradation, and these are: environmental technologies and policy stringency. While the reduction of emissions and resource consumption largely relies on innovative technologies, additionally, policy stringency plays a role in creating the necessary market, economic, and regulatory conditions for the adoption and dissemination of these technologies. Therefore, addressing it by including environmental innovation and the stringency of environmental policies is of great importance in balancing strategic frameworks in the pursuit of sustainable development.

In the literature, it is observed that the effects of environmental technologies and environmental policy stringency on environmental degradation are mostly not examined together. In only one study conducted by Güler and Doğan (2023), the interaction between policy and innovation was examined together, designed with a limited sample size and time frame. As a result, it has been determined that the joint consideration of environmental technologies and policy participation, as well as their impacts on environmental degradation, has not been sufficiently researched over a broader scope and longer time span that includes OECD countries. This research aims to address these gaps and contribute to the literature. In the study where tests were conducted using the panel data method with annual data from 38 OECD countries covering the years 1990-2022, analyses including fixed effects and Driscoll-Kraay (1998) estimators were performed, and a comprehensive assessment of long-term trends was presented.

Furthermore, this study looks into the combined effect of environmental technologies and policy strictness on carbon emissions and establishes a framework for the collaborative influence of regulatory factors on environmental outcomes.

2. Literature Review

The literature has two basic assumptions about the relation between technological development, economic growth, and degradation of the environment. The two hypotheses are the Environmental Kuznets Curve (EKC) and the Porter and van der Linde Hypothesis. The EKC, initially proposed by Kuznets (2019) to focus on income inequality and subsequently modified by Grossman and Krueger (1991), implies an inverted U-shaped relationship between economic growth and pollution. According to the EKC theory, environmental degradation increases during the early stages of economic growth before decreasing once a certain income level is achieved. This theory forms the base of Several studies exploring the relation between growth and damage to the environment. However, Porter and van der Linde (1995) argue that while regulations related to the environment may raise manufacturing costs at first, they may also encourage creativity and improve competitiveness in the long run. Porter and van der Linde claim that effective regulation of the environment could motivate businesses to create cleaner and more efficient technologies, enabling concurrent advances in economic and environmental performance.

According to several studies in the literature, environmental innovation and technology play an essential role in reducing environmental harm. Jebli et al. (2020) claim that switching to renewable energy sources and enacting energy efficiency laws are essential strategies in the fight against climate change. As stated by Jin et al. (2022), China’s policies promoting environmental innovation and human capital development have been effective in reducing carbon emissions in both the short and long term. Suki et al. (2022) state that the use of renewable energy and environmental innovation can significantly reduce carbon emissions and ecological footprints. Liu et al. (2022) draw attention to the geographical component of these processes, demonstrating that environmental innovation has a beneficial knock-on impact in nearby provinces in addition to lowering carbon intensity within areas. Similarly, Bilgili et al. (2025) state that increasing the use of renewable power and environmental technology may significantly reduce CO_2 emissions in Europe.

The importance of technological innovation is also emphasized through analyses across various countries. Wang et al. (2012) emphasized the importance of innovation in achieving a low-carbon economy, highlighting that patents in carbon-free energy technologies significantly reduce emissions. Samargandi (2017) emphasizes that GDP growth increases emissions in Saudi Arabia both in the short and long term, agricultural value added reduces emissions, and technological innovation shows limited efficiency gains. Similarly, Ganda (2019) states that although the use of renewable energy and R&D expenditures generally reduce emissions in OECD countries, certain forms of technological development may temporarily increase emissions, and the environmental impact of technology depends on the structure and maturity of the economy.

Recent research has enriched the literature by providing information concerning policy on renewable energy, economic complexity, and digitalization. Wang et al. (2020a) accentuate the promotion of green technologies and renewable energy to be used as strategies to contain emissions with almost equal rates of economic growth. Akyol and Mete (2021) confirm that even in OECD countries where energy use and economic growth are still the major causes of environmental degradation, emission reduction is significantly achieved through technology innovation. Su et al. (2021), in a study analyzing BRICS countries, found that while broadband and fixed-line internet led to high levels of emissions, the adoption of mobile technology reduces emissions. Adebayo et al. (2022) prove that information technology development in advanced economies like Denmark, Japan, and Sweden causes an increasing degree of energy efficiency and a decreasing level of emissions because of optimization effects. Similarly, Peng et al. (2022) point out that when countries' economic complexity goes beyond a certain value, emissions will reduce given advancement in technological capabilities as well as production efficiency. Albaker et al. (2023), using the quantile regression method on the MENA region, reveal that the use of renewable energy consistently decreases emissions at all income levels; however, green innovation and energy efficiency may, at the beginning, lead to an increase in emissions within low-quantile economies only. In alignment with this study, Zhao et al. (2024) posit that the digital economy bolsters the emission-reducing role played by green innovation; thus, showing how digital transformation strengthens environmental technology's effectiveness towards sustainability achievement.

Similar to the literature on technological innovation, awareness about the impact of EPS on environmental degradation is increasing. Ouyang et al. (2019) proved that EPS, in the case of OECD countries, contributes positively to environmental quality when regulatory thresholds are crossed and implies non-linear effects. According to De Angelis et al. (2019), stringent environmental regulations tend to favor innovation and sustainable growth in the long run after an initial cost disadvantage. This perspective reflects the Porter Hypothesis. Similarly, Wang et al. (2020b) demonstrate that stricter environmental policies capture more pollution and thus improve air quality, confirming the cost-channel mechanism of the hypothesis. Wolde-Rufael and Mulat-Weldemeskel (2020, 2021) show evidence in developing countries that expansion of EPS used in policy frameworks increases the proportion of renewable energy and decreases CO_2 emissions, albeit with an impact of differing magnitude depending on developmental stage. Wang et al. (2022) counters this by explaining the ineffectiveness of EPS through EPS's economic structure and technological capacity in developing economies. This suggests that the results of policies are influenced by the level of industrial sophistication in the country. Albulescu et al. (2022) introduce the temporal dimension by demonstrating asymmetrical effects whereby emissions are reduced with the tightening of policies, but an increase in the relaxation of policies has long-lasting negative impacts on the quality of the environment. Assamoi and Wang (2023) show that while EPS does enhance environmental performance, greater macroeconomic uncertainty can dampen that association, suggesting that certain stability conditions have a moderating impact. Frohm et al. (2023) further support this by demonstrating that EPS-related emission reductions are significantly higher in high-emission sectors, such as the energy and heavy industry, suggesting there is greater sectoral heterogeneity in the outcomes of policies. Last, Güler and Doğan (2023) indicate that innovation serves as a synergistic complement to EPS and that in combination, the two greatly improve emission reductions beyond what is possible by either alone.

The literature delineates patterns of complex interactions involving economic development, environmental technologies, and the stringency of enacted policies. The Porter Hypothesis emphasizes that strict environmental policies can promote environmental improvement by supporting innovation, while the Kuznets curve highlights that environmental degradation will increase in the early stages of development but will decrease once a certain income threshold is reached.

Overall, advancing environmental technologies, such as green innovation, digital development, and the use of renewable energy, help reduce emissions, while the importance of this effect depends on factors such as firm strength and economic complexity. As Porter pointed out, tough environmental rules encourage invention and decrease pollution, which helps innovation progress and supports sustainability. The form of environmental rules, economic balance, and varied levels of implementation among nations and industries can all influence how significant this impact is. To completely explain these disparities, institutional channels corresponding to aspects such as governance quality, institutional capability, and implementation variances must also be considered. In this context, the assessment of the literature covers findings from studies covering several nations and scopes, as well as studies on environmental technology and environmental policy stringency, which are consistent with the research's objective.

In conclusion, these findings highlight that the achievement of sustainable outcomes in the environment is dependent, in equal measure, on technological progress and policy architecture, and on the institutional structures that govern their interplays and execution. However, the body of research investigating the synergy of the impacts of environmental technologies alongside the impacts of the stringency of environmental policies on environmental degradation remains thin. Therefore, this research attempts to fill this void by pursuing a multidimensional framework that combines both the technological and policy dimensions to capture how innovation and policy stringency, in tandem, determine outcomes on the environment.

3. Methodology

This research is trying to assess the consequences of environmental technologies and the strength of environmental policy covering the years 1990 to 2022 for OECD countries. Since the analysis involves multiple countries over time, panel data is a suitable analysis for this study. Panel data, often referred to as data of a longitudinal nature, merges cross-sectional views with time-series trends by following multiple units (such as individuals, organizations, or nations) over time. This format allows researchers to observe differences between units and identify dynamic patterns that single cross-sectional or time-series datasets may miss. Panel data models offer several advantages, such as (Baltagi, 2005: 4-5); (i) Accounting for time-invariant unobserved heterogeneity, (ii) Panel data could utilize lagged variables to reflect dynamic behavior, (iii) The combination of information across two dimensions enhances efficiency and increases degrees of freedom.

In general, panel data analysis can be estimated through Fixed-effects (FE) and Random-effects (RE) estimators. The fixed-effects model controls for time-invariant unobserved heterogeneity by estimating unit-specific intercepts. This is suitable when the unobserved heterogeneity is linked to the explanatory factors. The assumption is that αi may be associated with xit, which means that ordinary least squares (OLS) estimates may be biased if this correlation is not properly addressed. The standard fixed effect model may be written as follows (Wooldridge, 2010: 9-10):

$$yit \;=\; \alpha i + \;\beta\, xit \;+\; \epsilon it \tag{1}$$

where; y_{it} is the dependent variable for unit i at time t, α_i is the unit-specific intercept, x_{it} are the explanatory variables, ϵ_{it} is the error term.

On the other hand, the Random Effects Model (RE), assumes that the specific effect for each individual αi is not related to the explanatory variables and treats it as a random draw, leading to more efficient estimates under exogeneity. The RE model is expressed as (Greene, 2012: 411):

$$y_{it} = \alpha + \beta x_{it} + \mu_{it} \tag{2}$$

$$\mu_{it} = \mu_i + \epsilon_{it} \tag{3}$$

The idiosyncratic error referred to as ϵ_{it}, whereas μi represents the random individual-specific component. RE outperforms FE if there is no association between μ_i and x_{it}. Otherwise, it produces biased results. There are two ways to estimate panel data (FE and RE), so to decide which way is more appropriate Hausman test is commonly used.

The Hausman test could be used to determine whether FE or RE is ideal for the estimated model. In addition, the Hausman test helps to inform whether the unit-specific effects are associated with the error term. If the unit-specific effects are not significantly associated with the error term, the random effects model is more relevant; however, the fixed effects model is the optimal way. The test equation below (Hausman, 1978):

$$H = (\beta\^RE - \beta\^FE)'[Var(\beta\^RE) - Var(\beta\^FE)] - 1(\beta\^RE - \beta\^FE) \tag{4}$$

A significant test statistic implies rejecting the null hypothesis in favor of the fixed effects model, indicating that the no-correlation assumption is violated.

Driscoll–Kraay (1998) standard errors are a robust covariance matrix estimator designed for linear panel data models. They extend heteroskedasticity and autocorrelation consistent estimators, such as Newey-West, to the panel data setting. A key advantage is that they provide consistent inference even when the error structure exhibits heteroskedasticity, serial correlation, and cross-sectional dependence. This makes them particularly suitable for macroeconomic panels with a relatively small number of cross-sections but a sufficiently large time dimension T. The regression model can be written as (Driscoll and Kraay, 1998):

$$y_{it} = \alpha_i + \beta x_{it} + \mu_{it}, i = 1 \ldots, N;\ t = 1 \ldots, T \tag{5}$$

where; y_{it} is the dependent variable, α_i is the he unit-specific fixed effects, x_{it} represents the explanatory variables, μ_{it} is the error term.

Driscoll–Kraay robust standard errors are widely used because they address several violations of the classical regression assumptions simultaneously. They remain valid in the presence of heteroskedasticity, where the variance of the error term differs across time or units; they also correct for autocorrelation, allowing for serial correlation of errors within panels, whether first-order or higher-order; and, unlike cluster-robust estimators, they explicitly account for cross-sectional dependence, capturing contemporaneous correlations of errors across units at the same point in time (Hoechle, 2007; Vogelsang, 2012).

4. Data & Model

This study used a combination of annual data of economic, environmental, and innovation-related variables, primarily sourced from the World Bank (2025) and the OECD (2025). Each variable is briefly explained below (Table 1).

Table 1. Data Explanation & Source

Variables Explanation	Variable	Source
Logarithm of GDP per capita	Ln-PERCAP	World Bank
Exports calculated as a proportion of GDP	EXP	
Manufacturing's contribution to GDP (%)	MFAC	
Fossil fuel energy consumption (% of total)	FFCON	
Electricity production from renewable sources, excluding hydroelectric (% of total)	EPFRS	
Government expenditure on education (% of GDP)	EXPOEDU	
Environmental degradation	CO2	OECD
Percentage of environmental patents	POINVT	
Patents on environmental technologies	POENVT	
Environmental Policy Stringency Index	EPS	

This study uses annual data between 1990–2022 for 38 OECD countries to investigate how environmental-related technologies and the strength of policy have an impact on carbon emissions. Panel data analysis was used to perform the empirical investigation. The analysis started with a correlation test to explore relationships among the dependent variables. The Hausman test was then applied to determine whether the fixed-effects or random-effects model was more suitable. The Wald test and the Wooldridge test were then used to check for heteroskedasticity and first-order autocorrelation, respectively. The results indicated the presence of both issues. In addition, formal tests for cross-sectional dependence could not be carried out because the data set was severely unbalanced. To account for possible dependencies within units, Driscoll–Kraay robust standard errors were employed, which are robust to both heteroskedasticity and autocorrelation as well as to cross-sectional correlation (Driscoll and Kraay, 1998; Hoechle, 2007):

$$CO_2 = \alpha_i + \beta\, Control\, Variables + \beta\, Explanatory\, Variables + \mu_{it} \qquad (6)$$

where the control variables include Ln-PERCAP, EXP, MFAC, FFCON, EPFRS, and EXPOEDU; and the explanatory variables are: POINVT, POENVT, and EPS. A detailed explanation of each variable is provided below:

CO2: This is the dependent variable and represents annual carbon dioxide emissions (in metric tons per capita) in each country obtained by dividing total national CO_2 emissions by the total population. It is an indirect measure of environmental degradation and is employed in the analysis as the primary independent variable.

Ln-PERCAP: It is the natural logarithm of GDP per capita (constant 2015 US dollars). The natural log is used to normalize the distribution of data, reduce skewness, and improve the measurement of proportional differences in income levels between countries.

EXP: This indicator represents the weight of exports in an economy. It is calculated by the total exports of goods and services as a percentage of gross domestic product GDP.

MFAC: It indicates the manufacturing value added percentage in a country's gross domestic product. It is worked out as the proportion of manufacturing value added to GDP, expressed as a percentage.

FFCON: This is a measure of the proportion of total energy use in which consumption comes from fossil fuels such as coal, oil, and gas. It is a measure of the proportion of energy that comes from fossil fuels within total energy usage.

EPFRS: This indicator demonstrates the share of electricity produced from renewable energy sources, excluding hydro. As a percentage of total electric production, not including hydropower, solar energy, wind power, and other non-hydroelectric renewables, contributes to that amount.

EXPOEDU: This indicator reflects the percentage of government expenditure on education as a ratio of GDP. This represents the level of public investment in education. It is included to explore possible indirect effects on environmental awareness and innovation capacity.

POINVT: Based on OECD data, this variable has been calculated by the percentage of green or environment-related patents relative to the total patenting activity in a country.

POENVT: This variable, obtained from the OECD, measures the number of patents specifically related to environmental technologies. It presents green technological advancement in each country and plays as a key indicator of environmentally associated technological steps

EPS: This index demonstrates the toughness of environmental-related regulations in each country. The higher the index value, the tougher the environmental policies.

Before proceeding with the analysis, it is helpful to provide a summary of each variable. Table 2 presents the descriptive statistics for the data.

Table 2. Summary Statistics of the Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
CO2	1212	8.771512	4.554696	1.13935	32.12177
Ln-PERCAP	1197	10.01643	0.855239	7.296311	11.80344
EXP	1235	44.30218	28.4783	8.81647	213.2227
MFAC	1128	15.42277	4.897782	3.912374	37.14683
FFCON	1254	74.37317	17.71773	10.25	100
EPFRS	1147	7.505317	12.42334	-69.5753	81.55761
EXPOEDU	1039	5.131914	1.16128	1.93433	8.58383
POINVT	1212	2.452989	6.00653	.000902	33.92035
POENVT	1136	10.38864	4.79643	0.9	50
EPS	1178	1.881909	1.177785	0	4.888889

Before proceeding with the analysis, demonstrating the graph between the dependent variable and explanatory variables will clarify the relationship between the dependent and explanatory variables. The graphics are like below (Figure 1).

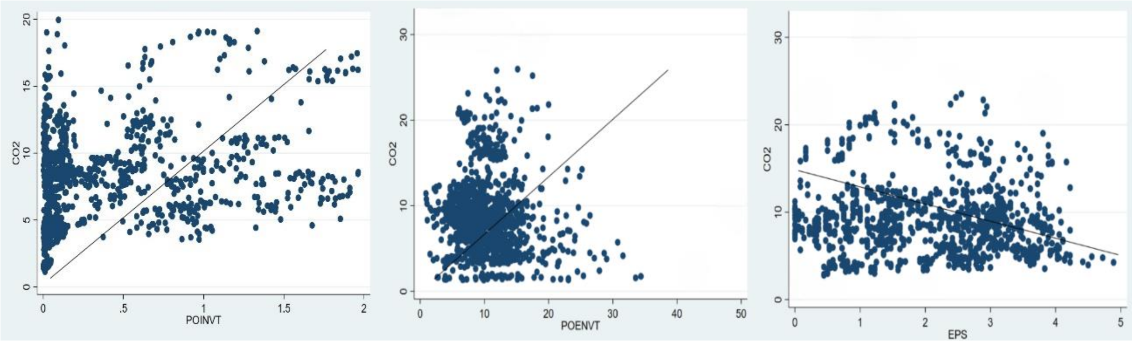

Figure 1. Time Series Plots of the Relationship Between CO2 and Environmental Technology, Environmental Policy Stringency Variables

Overall, Figure 1 suggests that while patents on environmental technologies (POENVT) and the percentage of environmental patents (POINVT) may contribute to higher emissions, the Environmental Policy Stringency Index (EPS) could be associated with emission reductions. These preliminary visual insights will be further examined in the statistical analysis.

Before proceeding with the analysis, a correlation test was conducted to check for potential multicollinearity. Table 3 presents the results of this test.

Table 3. The Results of Correlation Test

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	CO2	1									
2	Ln-PERCAP	0.43	1								
3	EXP	0.21	0.30	1							
4	MFAC	-0.15	-0.30	-0.00	1						
5	FFCON	0.30	-0.20	-0.02	0.12	1					
6	EPFRS	-0.29	0.24	0.08	-0.17	-0.28	1				
7	EXPOEDU	0.08	0.35	-0.05	-0.35	-0.45	0.25	1			
8	POINVT	0.29	0.21	-0.30	0.20	0.14	-0.09	-0.15	1		
9	POENVT	-0.10	-0.03	0.07	-0.17	-0.03	0.21	0.02	0.99	1	
10	EPS	0.04	0.58	0.31	-0.15	-0.09	0.34	0.10	0.25	0.23	1

According to the results of the correlation test, only one relatively high correlation was observed (between POINVT and POENVT). However, since these variables will be included in the model separately, this will not be considered a problem. The VIF test was performed to detect the absence of multicollinearity. VIF values of 5-10 may be a sign of moderate multicollinearity, while VIF exceeding 10 points to severe multicollinearity (Wooldridge, 2013: 98). As shown in the Table 4, all VIF values are far from exceeding these benchmarks; therefore, multicollinearity is not an issue for the estimated model.

Table 4. The Results of VIF Test

Variable	VIF	1/VIF	Variable	VIF	1/VIF
Ln-PERCAP	1.89	0.52785	Ln-PERCAP	2.13	0.469152
EPS	1.8	0.554889	EXPOEDU	1.69	0.590914
EXPOEDU	1.62	0.617715	EPS	1.61	0.620966
FFCON	1.33	0.752019	POINVT	1.58	0.630972
EPFRS	1.28	0.77984	EXP	1.48	0.675047
POENVT	1.28	0.78138	FFCON	1.34	0.743939
MFAC	1.28	0.78415	MFAC	1.33	0.751668
EXP	1.13	0.881412	EPFRS	1.24	0.80911
Mean/VIF	1.45		Mean/VIF	1.55	

Before proceeding to the estimation, the Hausman test needs to be estimated to decide if a fixed or random effects model is more suitable. The Hausman test results indicate that the fixed effects estimator is more suitable for the model used in this study. Given these findings, the results of the fixed effects estimation are presented Table 5.

Table 5. The Estimation Results of Fixed Effect

Variables	(1) CO2	(2) CO2	(3) CO2	(4) CO2	(5) CO2	(6) CO2
Ln-PERCAP	1.359***	1.202***	1.349***	1.747***	1.525***	1.748***
	(0.114)	(0.110)	(0.116)	(0.141)	(0.138)	(0.141)
EXP	-0.0297***	-0.0267***	-0.0286***	-0.0239***	-0.0212***	-0.0240***
	(0.00470)	(0.00450)	(0.00481)	(0.00484)	(0.00466)	(0.00484)
MFAC	0.205***	0.173***	0.205***	0.175***	0.149***	0.177***
	(0.0192)	(0.0187)	(0.0200)	(0.0204)	(0.0199)	(0.0205)
FFCON	0.117***	0.129***	0.116***	0.107***	0.120***	0.108***
	(0.00829)	(0.00802)	(0.00848)	(0.00848)	(0.00830)	(0.00851)
EPFRS	-0.0458***	-0.0375***	-0.0441***	-0.0425***	-0.0358***	-0.0426***
	(0.00491)	(0.00477)	(0.00504)	(0.00498)	(0.00486)	(0.00498)
EXPOEDU	0.186***	0.133**	0.176***	0.204***	0.151***	0.201***
	(0.0593)	(0.0569)	(0.0597)	(0.0590)	(0.0571)	(0.0591)
POINVT		0.217***			0.209***	
		(0.0231)			(0.0247)	
POENVT			0.00146			0.00908
			(0.00899)			(0.00900)
EPS				-0.340***	-0.281***	-0.353***
				(0.0705)	(0.0681)	(0.0716)
Constant	-15.90***	-15.20***	-15.73***	-18.29***	-17.17***	-18.43***
	(1.447)	(1.383)	(1.471)	(1.545)	(1.491)	(1.551)
Observations	941	941	904	904	904	904
R-squared	0.573	0.611	0.550	0.562	0.596	0.562
Number of Groups	38	38	38	38	38	38

Note: Standard errors in parentheses-*** $p<0.01$, ** $p<0.05$, * $p<0.1$

While the first model presents results only for the control variables, Models 2, 3, and 4 show the effects of the explanatory variables individually. Models 5 and 6 include the explanatory variables together. Since POINVT and POENVT are highly correlated, they were included in the model separately. Ln-PERCAP, MFAC, FFCON, EXPOEDU, and POINVT (Per capita income, manufacturing, fossil fuel energy consumption, Government expenditure on education, Percentage of environmental patents), all show positive and statistically significant effects on CO_2

emissions, which shows that economic growth and industrial activities, including fossil fuel energy consumption and manufacturing, contribute to environmental degradation. Electricity production from renewable sources (Green Energy Adoption) and exports has a negative and significant effect, confirming its role in reducing emissions. Environmental policy stringency also shows a negative and significant impact, suggesting that stronger regulations are effective. In contrast, the percentage of environmental technologies and patents on environmental technologies has statistically insignificant effects. Wald test indicates the presence of heteroskedasticity ($\chi^2(38) = 2111.80$, p = 0.0000) and Wooldridge test indicates the presence of first-order autocorrelation (F(1,37) = 637.944, p = 0.0000), in addition Durbin–Wu–Hausman test insured the absence of endogeneity Durbin (score) chi2(2) = 2.55151 (p = 0.2792); Wu-Hausman F (2,918) = 1.26412 (p = 0.2830). So, to address heteroskedasticity and first-order autocorrelation issues, the study applies Driscoll–Kraay estimation, which accounts for both problems effectively.

Table 6. The Estimation Results of Driscoll–Kraay

Variables	(1) CO2	(2) CO2	(3) CO2	(4) CO2	(5) CO2	(6) CO2
Ln-PERCAP	2.424*** (0.192)	1.700*** (0.126)	2.424*** (0.194)	3.077*** (0.192)	2.356*** (0.140)	3.150*** (0.166)
EXP	0.0214*** (0.00393)	0.0386*** (0.00511)	0.0223*** (0.00420)	0.0267*** (0.00467)	0.0465*** (0.00552)	0.0267*** (0.00456)
MFAC	-0.0825*** (0.0120)	-0.141*** (0.0170)	-0.0859*** (0.0127)	-0.0777*** (0.0117)	-0.143*** (0.0129)	-0.0699*** (0.0120)
FFCON	0.0932*** (0.00571)	0.0869*** (0.00629)	0.0933*** (0.00553)	0.0943*** (0.00586)	0.0875*** (0.00628)	0.0939*** (0.00629)
EPFRS	-0.113*** (0.00996)	-0.108*** (0.00977)	-0.110*** (0.00875)	-0.0946*** (0.00640)	-0.0876*** (0.00576)	-0.0979*** (0.00612)
EXPOEDU	0.532*** (0.101)	0.748*** (0.0905)	0.524*** (0.0923)	0.430*** (0.110)	0.654*** (0.0992)	0.430*** (0.121)
POINVT		0.190*** (0.0181)			0.208*** (0.0146)	
POENVT			-0.0270 (0.0280)			0.0442 (0.0268)
EPS				-0.898*** (0.0882)	-1.009*** (0.0891)	-0.968*** (0.0716)
Constant	-24.16*** (1.871)	-17.87*** (1.449)	-23.83*** (1.787)	-28.80*** (1.928)	-22.38*** (1.627)	-29.90*** (1.524)
Observations	941	941	904	904	904	904
R-squared	0.458	0.503	0.458	0.492	0.546	0.494
Number of Groups	38	38	38	38	38	38

Note: Standard errors in parentheses-*** p<0.01, ** p<0.05, * p<0.1

Table 6 shows the result of the Driscoll-Kraay with carbon dioxide emissions per capita CO_2 as the dependent variable. GDP per capita (Ln-PERCAP), exports (EXP), manufacturing activity (MFAC), and fossil fuel consumption (FFCON) all show positive, significant effects, indicating economic activity drives emissions. In comparison, electricity produced from renewable resources (EPFRS) has a consistent negative effect, suggesting a mitigating role in CO_2 emissions. Government expenditure on Education (EXPOEDU) affects emissions in a positive way, probably as a result of energy consumption in line with energy market development. The percentage of environmental-associated patents (POINVT) has a positive impact on CO_2, which possibly emphasizes initial stage costs, while the number of environmental-associated patents

(POENVT) demonstrates statistically insignificant impacts. The percentage of environmental patents (POINVT) unexpectedly shows a positive and significant effect, indicating that higher patent activity is linked with increased emissions. These unexpected results may mirror a time gap between new innovations and being adopted by the world (this means that the patents may be registered, but not yet adopted). Likewise, countries that have higher emissions may be registering more patents as an effective factor, not as a reflection of the new environmental innovations. Lastly, implementing the environmental-related rules and regulations slowly can lead to low levels of adoption, although a high level of innovation. However, the finding indeed considers that patents are not enough to widespread the technology, and environmental management is required to control the emissions. On the other hand, environmental policy strength (EPS) shows a strong, statistically significant, and negative effect, considering that strict policies play a game-changing role. This means that carbon dioxide emission control policies in OECD countries have been somewhat successful.

5. Conclusion

The present study has investigated the effect of environmental technologies and environmental policy stringency on carbon dioxide emissions across 38 OECD countries for the period 1990–2022 by utilizing a panel data technique. Both fixed effects and Driscoll–Kraay estimations were used to predict the relationship, also Wald and Wooldridge tests were conducted in order to identify respectively heteroskedasticity and first-order autocorrelation. The results consistently indicate that CO_2 emissions are positively associated with GDP per capita, exports, production of manufactures, consumption of fossil fuels, education expenditure, and percentage of environmental patents. On the other hand, renewable penetration and stringent environmental policies are helpful in reducing emissions.

The positive relationship between per capita GDP and emissions is consistent with the Kuznets (2019) hypothesis, which suggests that environmental degradation may increase in the early and middle stages of development as economies industrialize. On the other hand, the observed decrease in emissions with the implementation of stricter policies and the increase in renewable energy usage indicates a Kuznets curve-type turning point. In this context, the negative impact of economic growth on carbon emissions can be eliminated by appropriate policy and technology applications, covering elements such as income increase, structural reforms, and efficiency increase.

The results of the research show that in order for corporate performance and competitiveness to increase, innovation must be taken into the market efficiently. The positive relationship between environmental technologies and environmental degradation shows that just innovation itself does not lower environmental degradation. In this framework, Porter (1995) emphasizes the use of these technologies and the need for policies and corporate applications that increase the industrial applicability. The findings of this study cover Porter (1995) with this emphasis.

The conclusions drawn from this study are consistent with studies in the literature about the relationship between environmental degradation and economic growth and industrial activity (Jianu et al., 2022; Sikder et al., 2022; Cuerdo Mir and Luis Montes Botella, 2024; Dharmapriya et al., 2025). Specifically, GDP per capita, manufacturing activities, fossil fuel consumption, and education expenditures appear to have a positive impact on the CO_2 emissions. On the other hand, renewable energy use and environmental policy stringency significantly contribute to emission reduction. The result of this research emphasizes previous results of the literature regarding the critical role played by strict policy regulations and technological progress in achieving sustainable development aims (De Angelis et al., 2019; Albulescu et al., 2022; Güler and Doğan, 2023; Assamoi and Wang, 2023; Frohm et al., 2023). For this reason, new environmental-associated technological innovations alone are not enough to keep carbon dioxide under control. This suggests that policymakers should convert their interest from innovation promotion to creating conditions that could lead to the effective application of these innovations. Good environmental policies are essential for the widespread implementation of these innovations and the continued transition to renewable and green energy sources.

Corporate quality, governance capacity, and regulatory effectiveness are factors that could play a considerable role in the success of the policies that focus on environmental issues. Only with these factors will countries be able to have a wide implementation of environmental innovations in industry. Institutions that work in high quality are those that lead to more effective policies and regulations and help achieve a high level of integration of environmental innovation in the industry. Unlike these weak institutions impede this process. Therefore, further research should focus on examining the impact of environmental policies on environmental degradation by including institutional factors like governance indicators.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
The authors declare that they have contributed equally to the article.

Declaration of Researcher’s Conflict of Interest
There are no potential conflicts of interest in this study.

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