Heterogeneous impact of eco-innovation on premature deaths resulting from indoor and outdoor air pollution: Empirical evidence from EU29 countries

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Abstract: Environmental innovations play a vital role in reducing air pollution and the number of pollution-related mortality. Most of the previous studies have examined the role of eco-innovations in environmental quality. However, to our knowledge, no study has evaluated the effects of eco-innovation on air pollution as a cause of mortality. For this purpose, this research examines the effect of eco-innovations on premature deaths from indoor and outdoor air pollution in twenty-nine European countries from 1995 to 2019. The Method of Moments Quantile Regression (MM-QR) is used to assess the impacts. The results confirm the heterogeneous effects of the main variables in both models. Both models indicate that eco-innovations reduce premature deaths from outdoor and indoor air pollution, and these effects are more significant in high quantities (75th and 90th). Also, the effect of eco-innovations on reducing mortality due to indoor pollution is more significant than that related to outdoor pollution. Eco-innovation, economic growth, renewable energy consumption, and urbanization reduce premature mortality indoors and outdoors, but CO_2 emissions increase this mortality. The results of the Dumitrescu-Hurlin causality test also support that all variables, including eco-innovation and CO_2 emissions, have a bidirectional causal relationship with indoor (LIND) and outdoor (LOUT) mortality due to air pollution. Governments and politicians can help mitigate this problem by providing more environmental innovations by increasing support packages and reducing taxes.

Keywords: MM-QR model; Environmental innovation; Dumitrescu-Hurlin causality test; Indoor air pollution; Outdoor air pollution

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1. Introduction

By *outdoor air pollution*, we mean emissions caused by combustion processes from solid fuel burning, motor vehicles, and industry (NSW Government, 2022). According to Our World in Data (2022a), burning solid fuel sources like dung, crop waste, and firewood for heating and cooking

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generates *indoor air pollution*. Six pollutants play a significant role in creating outdoor and indoor air pollution. Namely *lead*, *particulate matters of different-size fractions*, *carbon monoxide*, *nitrogen dioxide*, *ozone*, and *sulfur dioxide* (Koengkan et al., 2022). Indeed, the outdoor and indoor air pollution caused by combustion processes are among the significant causes of global health problems (Our World in Data, 2022b). Moreover, according to Koengkan et al. (2022) and the World Health Organisation (WHO) (2018), these gases increase the risk of some of the world's most important causes of death (for example, stroke, lung cancer, heart disease, and respiratory diseases). Indeed, the health problems caused by indoor and outdoor air pollution tend to worsen in countries with higher incomes and transitioning from low to middle incomes (Koengkan et al., 2022).

According to Our World in Data (2022b), in 1990, outdoor air pollution accounted for 2.14 million premature deaths. In 2017, this value reached 3.41 million deaths globally. In some countries, outdoor air pollution accounts for more than (8%) of deaths. For example, in Egypt, outdoor air pollution accounted for (12%) of deaths in 2017; the percentage of deaths caused by this air pollution was (10%) in China and Turkey and equal to (8%) in India in the same period. On the other hand, indoor air pollution was responsible for 2.71 million deaths worldwide in 1990. In 2017, it was responsible for 1.64 million deaths (Our World in Data, 2022a). Moreover, indoor air pollution accounts for (6%) of premature deaths in low-income countries. In 2017, this range was from less than (1%) across most of North America and Europe to approximately (11%) in Papua New Guinea, with more than one in ten deaths.

In 1990, outdoor air pollution caused (6.72%) of premature deaths in the European Union (EU). This value reached (3.71%) in 2019. In the same years, indoor air pollution was responsible for (1.05%) and (0.19%) of premature deaths in 1990 and 2019. These are shown in **Figure 1** below.

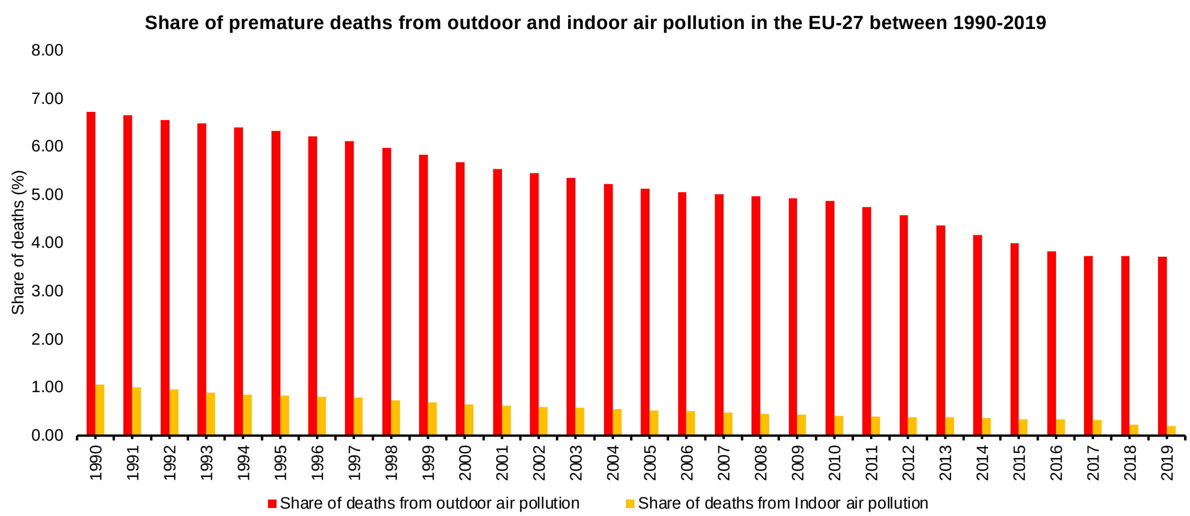

Figure 1. Share of premature deaths from indoor and outdoor air pollution in EU-27, between 1990 and 2019. This figure was created using Our World in Data (2022a,b).

In other words, there was a reduction of (-45%) in the share of premature deaths resulting from outdoor air pollution between 1990 and 2019 and a reduction of (-82%) in the share of premature deaths resulting from indoor air pollution in the same period. Indeed, the decline in the share of premature deaths resulting from indoor and outdoor air pollution is related to initiatives to mitigate air pollution in EU countries (for example, eco-innovative initiatives, electrification of road transport, and energy transition) (European Environmental Agency, 2021). In fact, according to Eurostat (2022), the exposure to the air pollutant $PM_{2.5}$, an important particulate matter, has dropped by fourteen percent in EU-27. This result is shown in **Figure 2** below.

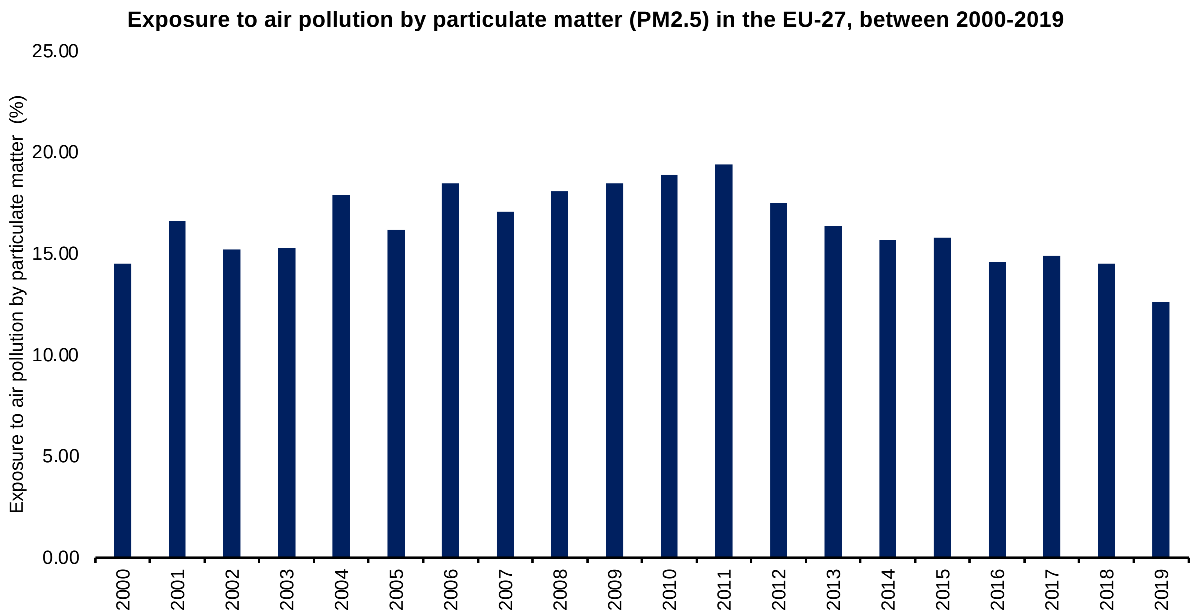

Figure 2. Share of premature deaths resulting from indoor and outdoor air pollution in the European Union (EU) between 1990 and 2019. This figure has been created using data from Eurostat (2022).

As shown in **Figure 2** above, the exposure to air pollution by particulate matter ($PM_{2.5}$) was (14.5%) in 2000, and this value dropped to (12.60%) in 2019. According to European Environmental Agency (2021), this reduction mitigated premature deaths attributed to air pollution in EU-27 by (33%) in 2019. Therefore, if air quality continues to improve and the number of premature deaths per year continues to fall at a comparable rate, then the zero-pollution target will be achieved by 2032.

The main concern is to reduce the exposure of poorer residents of the EU to air pollution. These people live next to industrial areas or busy roads and, as a result, are exposed to higher levels of air pollution. In some European cities, central areas, which are also more polluted, are inhabited by wealthier people. On the other hand, in some other cities, poorer communities live in central areas (European Environmental Agency, 2021). Moreover, in some Eastern and South-eastern Europe countries, regions with lower Gross Domestic Product (GDP) per capita are further exposed to $PM_{2.5}$. This situation is mainly caused by the combustion of solid fuels of low quality, like wood and coal, for domestic heating in low-efficiency ovens. Therefore, in particular regions, the higher exposure of the population to $PM_{2.5}$ leads to a more significant number of premature deaths caused by air pollution, consequently generating increased economic costs. Moreover, according to Europa (2020), the economic costs of premature deaths from air pollution are well over €20 billion per year in the EU.

The European Commission is committed to reducing air pollution to minimize environmental and human health risks. However, mitigating exposure to air pollution is a systemic, complex challenge that needs the concerted action of economic sectors and political and societal actors. Several governments, cities, and businesses have implemented eco-innovative solutions like pioneering ways to reduce pollution from farming practices, advanced household heating technologies, or strategic urban mobility plans (Europa, 2020).

In the EU, green and eco-innovation technologies are essential to the future. Indeed, the economic prosperity of the EU is intrinsically related to preserving its environment and the global demand for resource-efficient solutions and renewable energy. Moreover, it will be a source of economic growth and jobs in the forthcoming years (Europa, 2022a). The growth of the environment industry by more than fifty per cent in the period from 2000 to 2011 reveals that green industries are booming. In the EU, more than three million people are employed by eco-industries. Also, European businesses supply one-third of the global green technologies market, a market with a current worth of €1 trillion, which is expected to double in five years. This issue shows the great potential of eco-innovation to drive economic growth and jobs and mitigate environmental degradation in the region (Europa, 2022a).

Indeed, in 1990, the share of patents on environmental technologies (% of all technologies) was (7.61%). In 2019, this reached the value of (14.09%). This result is shown in **Figure 3** below. This situation shows that the EU region's green industries and eco-initiatives are booming, as Europa (2022a) mentioned.

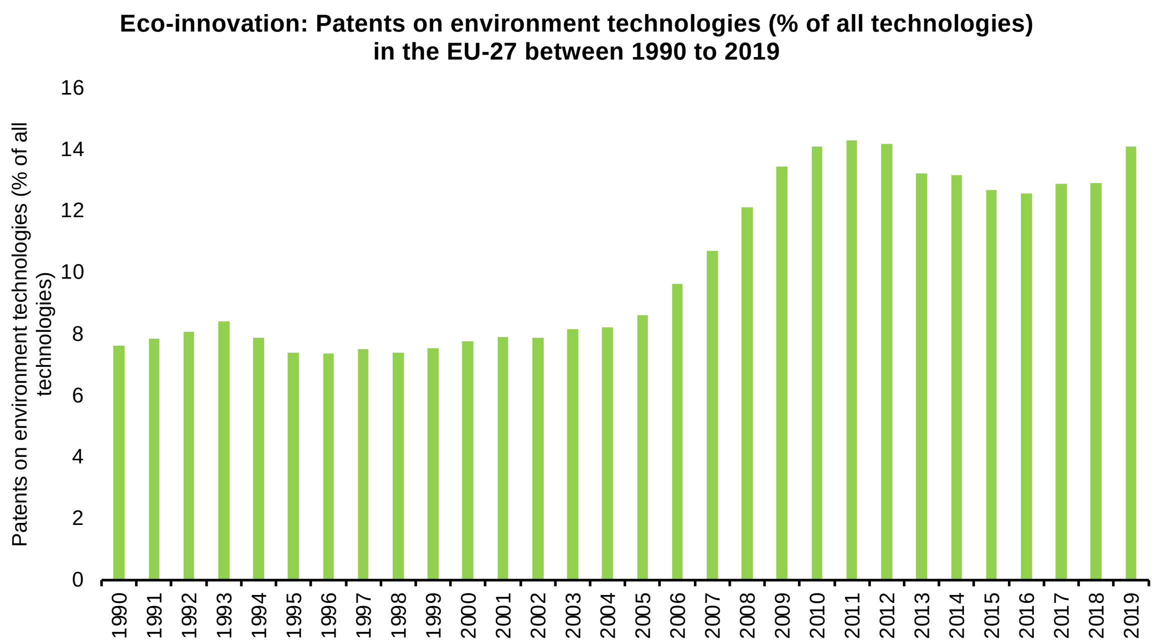

Figure 3. Eco-innovation: Patents on environment technologies (% of all technologies) in EU-27 from 1990 to 2019. This figure has been created using data from OECD DATA (2022).

Therefore, due to the evidence, eco-innovative initiatives are booming in the EU through patents of environmental technologies. Understanding their possible impact on indoor and outdoor air pollution deaths is necessary.

As far as we know, most of the literature examined the impact of eco-innovation projects on reducing air pollution or carbon dioxide (CO_2) emissions (for example, Alam et al., 2021; Cheng et al., 2021; Ahmad et al., 2021; Meirun et al., 2021; Hasanov et al., 2021; Abid et al., 2021; Dauda et al., 2021; Chen and Lee, 2020; Wang and Zhu, 2020; Khattak et al., 2020; Koçak and

Ulucak, 2019; Petrović and Lobanov, 2019; Hashmi and Alam, 2019; Cheng et al., 2019a; Cheng et al., 2019b; Du et al., 2019; Ganda, 2019; Dauda et al., 2019; and Fernández et al., 2018). Indeed, if environmental innovations can reduce air pollution or CO_2 emissions, these plans could reduce premature indoor and outdoor air pollution deaths. Accordingly, there is a gap in the literature regarding the possible link between eco-innovation initiatives and reducing premature deaths from indoor and outdoor air pollution. For this reason, the present research aims to fill the gap mentioned above by analyzing the impact of eco-innovation initiatives on premature deaths resulting from indoor and outdoor air pollution. We will answer this question by conducting a macroeconomic analysis using a panel with data from twenty-nine European countries from 1995 to 2019. Ordinary least squares (OLS) methods with fixed effects, moments quantile regression (MM-QR), and the Dumitrescu-Hurlin causality test will be used.

The innovations of this study and its contribution to the literature can be described as follows. (i) This investigation, as a pioneering effort, examines the impact of eco-innovation on premature deaths from indoor and outdoor air pollution in twenty-nine European countries from 1995 to 2019. As mentioned in this introduction, such an investigation has not been done before. (ii) The effects of environmental innovation on mortality due to indoor and outdoor pollution have been studied separately, and the results have been compared. (iii) This investigation introduces novel econometric models, namely, OLS with fixed effects, the MM-QR model, and the Dumitrescu-Hurlin causality test. (IV) Given that most European countries have ambitious goals to reduce CO_2 emissions, investing in green innovation is one of the main policies. To this end, this research supports policymakers in developing coherent initiatives that offer innovative environmental solutions to improve the environment.

The remainder of this paper is divided into five sections, described as follows. **Section 2** presents a brief review of the literature. **Section 3** discusses the methods and presents the data. **Section 4** is devoted to the empirical results, and **Section 5** discusses the obtained results. Finally, **Section 6** presents the policy implications and conclusions.

2. A brief review of the literature

This section is devoted to reviewing previous studies in environmental innovation. Our studies show that the effects of eco-innovations on mortality due to air pollution have not been studied so far. As a result, we evaluated those research papers that examined the relationship between air pollution and eco-innovation. These include Alam et al., 2021; Cheng et al., 2021; Ahmad et al., 2021; Meirun et al., 2021; Hasanov et al., 2021; Abid et al., 2021; Dauda et al., 2021; Chen and Lee, 2020; Wang and Zhu, 2020; Khattak et al., 2020; Petrović and Lobanov, 2020; Koçak and Ulucak, 2019; Hashmi and Alam, 2019; Cheng et al., 2019a; Cheng et al., 2019b; Du et al., 2019; Ganda, 2019; Dauda et al., 2019; and Fernández et al., 2018.

Countries have recently paid special attention to environmental innovations to reduce environmental impact. Because environmentally friendly innovations bring maximum economic growth at the lowest environmental cost. These innovations include pollution prevention, energy saving, waste recycling, and environmental management. (Shao et al., 2021; Ali et al., 2022). Renning (2000) states that environmental innovation involves new processes, practices, or systems contributing to environmental improvement and sustainability. It also argues that cleaner technologies can reduce environmental pollution and minimize the overuse of resources (Dauda et al., 2021; Mongoet al., 2021). Environmental innovation also positively affects the ecosystem due to green energy and reducing fossil fuel consumption. In addition, these technologies can help countries improve the efficiency of their production processes and increase more sustainable and environmentally friendly services (Mongoet al., 2021). In addition to saving energy and efficiency, environmental innovations use various environmentally friendly energy sources and help economies reduce carbon emissions (Pan et al., 2021). Considering that carbon dioxide emissions increase environmental pollution, they have negative effects on human health in two ways: first, inhaling high CO_2 concentrations damages directly the respiratory system and causes lung cancer, asthma exacerbation, and death by respiratory and heart diseases (Koengkan et al., 2021; Ahmad et al., 2021). Therefore, eco-innovations can reduce air pollution mortality by saving energy and reducing carbon emissions. In their study of thirty OECD countries, Alam et al. (2021) examined the effects of R&D investment on environmental quality and clean energy consumption from 1996 to 2013. They found the positive effect of R&D investment on clean energy consumption while reducing CO_2 emissions. Cheng et al. (2021) examined the impact of technological innovations on CO_2 emissions in thirty-five OECD countries from 1996 to 2015. In this study, the quantile panel model was used. The results showed the effectiveness of technological innovation in reducing CO_2 emissions.

Ahmad et al. (2021) explained the effects of innovation shocks on environmental quality in twenty-six OECD countries during the period 1990-to 2014. According to their results, negative shocks reduce the environmental quality, while positive shocks improve the environment. Meirun et al. (2021) explored the effects of green technology innovation on economic growth and CO_2 emissions in Singapore from 1990 to 2018. Their results revealed that these innovations increase economic growth in the long run while reducing CO_2 emissions.

According to Hasanov et al. (2021), in a survey concentrated on the BRICS countries, technological advances reduce CO_2 emissions. Abid et al. (2021) studied the G8 countries and examined the effects of technological innovation on environmental quality. Their results revealed a negative and long-term relationship between technological innovation and CO_2 emissions. The empirical results of a survey performed by Dauda et al. (2021) on nine African countries from 1990-to 2016 indicated a U-inverse relationship between CO_2 emissions and eco-innovation. Chen and Lee (2020) used the spatial econometrics model to study ninety-six countries. According to their results, these innovations do not significantly impact the worldwide reduction of CO_2 emissions. However, technological innovations in countries with higher incomes significantly reduce CO_2 emissions.

Wang and Zhu (2020) used a spatial econometric model to examine how energy technology innovations affect the reduction of CO_2 emissions. The results confirmed the impact of renewable energy technology innovation on reducing CO_2 emissions. Furthermore, according to the Kuznets framework, Khattak et al. (2020), in a survey of BRICS economies from 1980-to 2016, verified the reduction of CO_2 emissions in India, South Africa, China, and Russia, except Brazil, as a result of innovative activities. Finally, Petrović and Lobanov (2020) studied the effect of R&D spending on CO_2 emissions in sixteen OECD countries from 1981 to 2014. Their results confirmed the impact of R&D expenditures on reducing CO_2 emissions on average.

Nevertheless, it was shown that these costs positively affected CO_2 emissions in (40%) of the countries. Finally, Koçak and Ulucak (2019) used the dynamic panel model to examine the impact of energy innovation on CO_2 emissions in nineteen OECD countries with high incomes. The authors found a non-significant relationship between reduced CO_2 emissions and renewable energy innovations.

Hashmi and Alam (2019) discussed the effects of innovation and environmental regulation on CO_2 emissions in OECD countries from 1999-to 2014. According to their results, environmental tax is more effective in reducing CO_2 emissions. The reason is that a (1%) increase in innovation (respectively, environmental tax) causes a (0.017%) (respectively, 0.03%) reduction in CO_2 emissions. Cheng et al. (2019a) used a quantile panel model to investigate the impact of innovation on CO_2 emissions. Their findings suggest that innovation has small and positive effects on CO_2 emissions. Cheng et al. (2019b) examined the heterogeneous effects of environmental innovations on CO_2 emissions in the BRICS countries using the quantile panel model. Using the threshold panel model, they found negligible, positive heterogeneous effects of eco-innovations on CO2 emissions at 90th and 95th in seventy-one countries. Du et al. (2019) show that in countries with lower income thresholds, eco-innovations have a non-significant effect on reducing CO_2 emissions. However, in countries with higher incomes, these have a significant, negative effect on CO_2 emissions. Also, in selected OECD countries, Ganda (2019) found different effects of innovation and technology investments on CO_2 emissions.

Moreover, the findings revealed the potential of these factors in reducing CO_2 emissions. Dauda et al. (2019) surveyed eighteen developing and developed countries in different regions (G6, MENA, BRICS). Their findings revealed that innovation reduces CO_2 emissions in G6 countries and increases CO_2 emissions in BRICS and MENA countries. In a study of fifteen countries, the United States, the European Union, and China, Fernández et al. (2018) showed the reduction of CO_2 emissions due to innovations in developed countries.

As discussed so far, various studies in diverse regions and countries have investigated how eco-innovation affects environmental quality using different models. However, as far as we know, no study has been conducted on the effects of environmental innovation on reducing premature deaths from indoor and outdoor air pollution. On the other hand, in this research, one of the newest econometric methods (the MM-QR) is used to investigate the heterogeneous effects of the main variables on air pollution mortality. The following section introduces the data/variables and the methodology used in our study.

3. Data and the utilized methods

This section addresses the data/variables and the methods we used to conduct this investigation. Therefore, we present the longitudinal data, i.e., variables and countries, in Subsection 3.1, while in Subsection 3.2, we describe the research methods. This investigation used the econometric techniques (i) *ordinary least squares (OLS) with fixed effects* and (ii) *moments quantile regression (MM-QR).*

3.1. Data

In order to analyze the impact of eco-innovation initiatives on premature deaths from indoor and outdoor air pollution, twenty-nine countries from Europe were selected: Denmark, France, Hungary, Bulgaria, Greece, Belgium, Latvia, Germany, Lithuania, Cyprus, Norway, Poland, Finland, Iceland, Austria, Ireland, Croatia, the Netherlands, Italy, Portugal, Luxembourg, Slovakia, Romania, Spain, Czechia, Slovenia, the United Kingdom, Sweden, and Estonia. Furthermore, the period from 1995 to 2019 was used.

These twenty-nine countries were selected because, as mentioned in the introduction, the European countries have registered a boom in eco-innovative initiatives, and it is needed to understand the possible externalities of this boom. Furthermore, this research used data from 1995 to 2019 because Our World in Data (2022) provided data for the variables IND and OUT until 2019. **Table 1** below shows the variables used to conduct this research.

Table 1. Variable acronyms, descriptions, and sources

Variable acronyms	Variable descriptions	Sources
Dependent variables		
OUT	Death rates resulting from outdoor air pollution measure the number of deaths per 100,000 population.	Our World in Data (2022)
IND	Death rates resulting from indoor air pollution measure the number of deaths per 100,000 population.	Our World in Data (2022)
Independent variables		
CO_2	CO_2 emission tonne per capita.	British Petroleum (BP) (2022)
PATENT	Eco-innovation initiatives. This variable includes patents on environment technologies (% of all technologies).	OECD DATA (2022)
GDP	Gross domestic product (GDP) per capita (constant = 2010 $).	World Bank Data (WBD) (2022)
REN	Renewable energy consumption tonne per capita.	British Petroleum (BP) (2022)
URB	Urban population = % of total population.	World Bank Data (WBD) (2022)

Therefore, this empirical investigation will use the variables OUT, IND, CO_2, PATENT, GDP, REN, and URB. The variables OUT and IND are the dependent variables of this investigation. At the same time, PATENT, GDP, REN, and URB are the independent variables. Moreover, some authors, including Koengkan et al., 2022 and Koengkan et al., 2021, used OUT and IND as dependent variables. The same occurred to the variables CO_2, GDP, REN, and URB that were already used as independent variables in the literature to explain OUT and IND (see Koengkan et al., 2022 and Koengkan et al., 2021). However, as far as we know, none of the studies has used the variable PATENT to explain the variables OUT and IND. Therefore, the use of this variable is a novelty.

After briefly introducing the variables, we need to describe the methods utilized in this study. Moreover, in this investigation, all variables will be transformed into natural logarithms (L) to linearise the relationships between model variables.

3.2. The methods

The present subsection describes the methods that we used in our empirical investigation. Therefore, this empirical investigation will follow the following strategy that numerous authors used (e.g., Koengkan et al., 2022; Koengkan et al., 2021, and Fuinhas et al., 2021). **Figure 4** below reveals the methodological strategy used in this investigation.

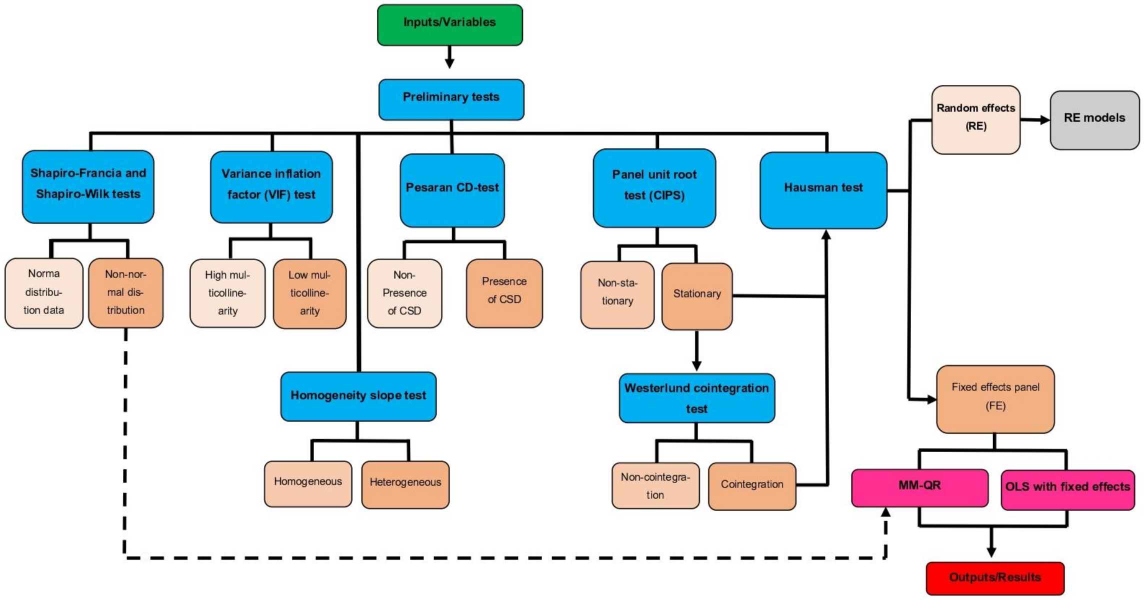

Figure 4. Method strategy. The authors created this figure.

As seen in **Figure 4**, the empirical approach follows rigorous criteria beginning with preliminary tests assessing the series' characteristics. Then, respecting the series' properties, the adequacy of econometric techniques and the quality of estimated models (OLS with fixed effect, and MM-QR) were tested. These procedures assure the reliability of empirical research.

3.2.1. The method of moments quantile regression (MM-QR)

Machado and Silva (2019) developed the MM-QR to capture unobserved distributional heterogeneity across countries within a panel (Koengkan et al., 2022). Moreover, as Fuinhas et al. (2021) mentioned, the method assumes that the covariate only affects the variables via the location channel. Furthermore, it examines the conditional heterogeneous covariance effects of the determinants of premature deaths resulting from indoor and outdoor air pollution in different quantiles. Therefore, the MM-QR can be defined as follows.

$$Q_{it}(\tau|X_{it}) = \left(\alpha_i + \delta_i q(\tau)\right) + y'_{it}\beta + Z'_{it}\gamma q(\tau). \quad \textbf{(1)}$$

Herein, $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$ is a scalar coefficient that denotes the quantile- τ fixed effects for an individual country. Since it is not location-fixed, the distributional impact varies from the classical fixed effect (Fuinhas et al., 2021). Moreover, time-invariant traits, depicted by the distribution impact, allow other variables to affect the investigated countries in various ways (Machado and Silva, 2019).

3.2.2. Ordinary least squares (OLS) with fixed effects

This investigation used OLS with fixed effects to verify the MM-QR results. This option means that the method will be used as a robustness check. Fuinhas et al. (2021) mentioned that OLS with fixed effects estimates the mean response for the fixed predictors and the slope and intercepts for observations. Moreover, OLS results with fixed effects are similar to those obtained using the 50th quantile of MM-QR, as Koengkan et al. (2022) mentioned. Therefore, the typical definition of OLS with fixed effects is as follows.

$$a_{it} = \beta_0 + \beta_1 y + \beta_2 y + \beta_3 y + \cdots + \varepsilon_{it}. \quad \textbf{(2)}$$

Here, β denotes the value of fixed covariates, which is fitted to predict the dependent variable a_{it}. Also, β_0 and ε_i denote the intercept and the error term, respectively. Moreover, each variable enters the regression for country *i* at year *t*.

Before realizing model estimations, preliminary tests were performed to assure the correctness of the econometric approach. **Subsection 3.2.3** describes the initial.

3.2.3. Preliminary tests

As mentioned above, we need to compute preliminary tests to identify the characteristics of variables and the existence of singularities (Fuinhas et al., 2021). Therefore, the following tests must be computed (see **Table 2** below).

Table 2. The preliminary tests used in this research

Type of the test	Finality
Shapiro-Wilk (Shapiro and Wilk, 1965) Shapiro-Francia (Shapiro and Francia, 1972)	These tests check the presence of normality in the panel model.
Variance Inflation Factor (VIF) (Belsley et al., 1980)	This test identifies the presence of multicollinearity between the variables of the model.
Cross-sectional dependence (CD) (Pesaran, 2004)	This test checks the presence of cross-sectional dependence in the model's variables.
Slope Homogeneity test (Pesaran and Yamagata, 2008)	This test checks the presence of slope homogeneity in the model.
Panel Unit Root test (CIPS) (Pesaran, 2007)	This test identifies the presence of unit roots in the variables.
Westerlund test (Westerlund, 2007)	This test identifies the presence of cointegration in the variables that are I(I).
Hausman (Hausman, 1978)	The finality of this test is to confront the models' random effects versus fixed effects and heterogeneity.

The econometric software **Stata 17.0** was used. More specifically, the Stata commands used in this study included *sktest, sum, xtcd, swilk, vif, multipurt, xtwest with option constant, xthst, xtqreg, hausman,* and *xtreg*. These commands were used to realize the preliminary tests and estimate the model. In what follows, we describe the empirical results of our study.

4. Empirical results

To check the robustness of the main model, we present the empirical results obtained using the preliminary tests, the MM-QR and OLS with fixed effects. Therefore, in **Subsection 4.1**, we present the results of the preliminary tests. In contrast, in **Subsection 4.2**, we discuss the results obtained using the models of OLS with fixed effects and MM-QR.

4.1. Preliminary tests

Table 3 below shows the statistical characteristics of the variables. According to the table, the total number of observations is 725. Moreover, the average number of premature deaths from indoor air pollution is 3.3, while that of premature deaths from outdoor air pollution is 32.1. These results also show that the minimum and maximum ratios of the variable environmental technology inventions (Proxy of eco-innovation initiatives) are 0.84 and 31.6, respectively.

Table 3. Descriptive statistics of the variables

Variables	Descriptive statistics				
	Obs.	Mean	Std.-Dev.	Min.	Max.
OUT	725	32.08705	22.48283	2.643612	127.6525
IND	725	3.29793	6.727683	0.0087768	45.32486
CO_2	725	8.404411	3.923589	2.914405	27.51753
PATENT	725	10.33236	4.775387	0.84	31.58
GDP	725	33122.23	22655.35	3784.078	111968.4
REN	725	1.174155	2.017607	0	12.39415
URB	725	72.04486	12.18446	50.622	98

Notes: Max and Min denote the maximum and minimum, respectively; Std.-Dev. and Obs. denote the model's standard deviation and the number of observations.

Indeed, having introduced the descriptive statistics of the variables, we needed to check the normality of the data. To this end, the Shapiro-Wilk (Shapiro and Wilk, 1965) and Shapiro-France (Shapiro and Francia, 1972) tests were computed. The normal distribution of data was the null hypothesis of the tests. **Table 4** shows the results obtained using the normal distribution tests.

Table 4. Normal distribution tests

Variables	The Shapiro-Wilk test Statistic		The Shapiro-Francia test Statistic		Obs.
LOUT	0.97926	***	0.98023	***	725
LIND	0.93591	***	0.93763	***	725
LCO_2	0.98924	***	0.99000	***	725
LPATENT	0.94397	***	0.94355	***	725
LGDP	0.97230	***	0.97353	***	725
LREN	0.93049	***	0.92965	***	725
LURB	0.97756	***	0.97583	***	725

Notes: *** denotes statistical significance at the (1%) level; "L" represents the natural logarithm.

As shown in **Table 4** above, the null hypothesis on the normality of data was rejected by all the variables. Therefore, it was necessary to identify the presence of multicollinearity between the model's variables after identifying the presence of non-normally distributed data. Thus, the variance inflation factor (VIF) (Belsley et al., 2005) was computed. **Table 5** below presents the VIF test results for the two models. Therefore, the VIF test was checked for Model I, with LOUT as the dependent variable, and in Model II, LIND as the dependent variable.

Table 5. The VIF test

Variables	Model I Dependent variable (LOUT) VIF-test		Variables	Model II Dependent variable (LIND) VIF-test	
	VIF	Mean VIF		VIF	Mean VIF
OUT	n.a.		IND	n.a.	
LCO_2	1.91		LCO_2	1.91	
LPATENT	1.02	1.64	LPATENT	1.02	1.65
LGDP	2.03		LGDP	2.04	
LREN	1.49		LREN	1.49	
LURB	1.74		LURB	1.74	

Notes: n.a. denotes *not available*.

Table 5 above indicates the absence of multilinearity in both models, where the VIF value for each variable is less than the standard 10, and the VIF average is less than 6. Therefore, we checked the presence of cross-sectional dependence and the heterogeneity slope (HS) in panel data after identifying the presence of low multicollinearity in both models. Thus, the Pesaran CD-test (Pesaran, 2004) and the HS-test (Pesaran and Yamagata, 2008) were computed. The null-hypothesis was cross-sectional independence. The Pesaran CD and HS-test results are shown in **Table 6** below. Indeed, the Pesaran CD-test was individually computed in each variable. In contrast, the HS-test for Model I and Model II was computed.

Table 6. Pesaran CD and HS tests

Pesaran CD-test		
Variables	CD-Statistics	p-value
LOUT	97.29^{***}	0.000
LIND	99.01^{***}	0.000
LCO_2	43.36^{***}	0.000
LPATENT	33.69^{***}	0.000
LGDP	82.36^{***}	0.000
LREN	32.21^{***}	0.000
LURB	26.78^{***}	0.000
Homogeneity Slope test		
Models	Delta	Adjusted Delta
Model I	24.540^{***}	29.064^{***}
Model II	22.127^{***}	26.206^{***}

Notes: *** denotes statistical significance at the (1%) level.

Table 6 shows that in all model variables, cross-section dependence is present. Moreover, the HS-test points to slope heterogeneity in the models, where delta and adjusted delta are statistically significant. Therefore, after confirming slope heterogeneity in the models and cross-section dependence in the variables, we needed to find the unit root in the variables. Thus, the CIPS test (Pesaran, 2007) was computed. **Table 7** below shows the results of the panel unit root test.

Table 7. Panel unit root test

Variables	Panel Unit Root test (CIPS) (Zt-bar)		
	Without trend		With trend
	Lags	Adjusted t	Adjusted t
LOUT	1	-2.987 ***	0.811
LIND	1	-0.596	-1.800 **
LCO_2	1	-0.979	-2.353 ***
LPATENT	1	-10.697 ***	-9.299 ***
LGDP	1	-2.375 ***	-1.375 *
LREN	1	-2.238 **	-1.791 **
LURB	1	-3.11 ***	-2.341 ***

Notes: ***, ** and * denote statistical significance at (1%), (5%), and (10%) levels, respectively.

LOUT, LIND, and LCO_2 are on the boundary between the I(0) and I(1) orders of integration, as the panel unit root test indicated. That is, they are quasi-stationary. However, the variables LPATENT, LGDP, LREN, and LURB are stationary or of I(1) order of integration. Therefore, it was necessary to identify the presence of cointegration in the presence of stationarity variables in the model. Thus, the Westerlund panel cointegration test (Westerlund, 2007) was computed. The absence of cointegration in the variables was the null hypothesis of this test. **Table 8** shows the results of the Westerlund test. In this investigation, the cointegration test was used in the variables LPATENT, LGDP, LREN, and LURB. The Westerlund test requires all the variables to be of I(1) order of integration.

Table 8. The Westerlund panel cointegration test

The variables LPATENT, LGDP, LREN, and LURB			
Statistic	Value	Z-value	Robust P-value
Gt	-3.461	-7.015	0.000 ***
Ga	-9.349	1.238	0.080 *
Pt	-28.247	-16.942	0.000 ***
Pa	-14.289	-5.609	0.000 ***

Notes: *** and * denote statistical significance at (1%) and 10% levels, respectively; Pt and Pa test the cointegration of the panel. Also, Gt and Ga individually test the cointegration for each country.

The results of the Westerlund cointegration test reveal that the variables LPATENT, LGDP, LREN, and LURB are cointegrated, where the null hypothesis can be rejected. After realizing the cointegration test, it was necessary to identify the presence of random effects versus fixed effects and heterogeneity in Models I and II. Thus, the Hausman test was computed. This test's null hypothesis considered the random effects as the best estimators. **Table 9** below shows the results of the Hausman test in Model I and Model II.

Table 9. The Hausman test

Models	Chi2(5)	Prob.
Model I	123.63***	0.000
Model II	23.45***	0.000

Notes: *** denotes statistical significance at (1%) level.

The results of the Hausman test indicate that fixed effects are present in the models, where the null hypothesis can be rejected. Moreover, this presence is required to calculate OLS with fixed effects and the MM-QR. In this subsection, we presented the results of the preliminary tests. The results of OLS with fixed effects and the MM-QR will be presented in the following subsection.

4.2. *The results* of *OLS with fixed effects and* the *MM-QR*

This subsection presents the results of OLS with fixed effects and the MM-QR. The results of OLS with fixed effects and the MM-QR from Model I, where the dependent variable is LOUT, are shown in **Table 10** below.

Table 10. Estimation results of the MM-QR regression model and OLS with fixed effects (**Model I**)

Independent variables	The main method					Robustness check
	MM-QR					OLS
	Model I-Dependent variable (LOUT)					
	Quantiles					Fixed Effects
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	
LCO_2	0.94766 ***	0.9308 ***	0.9093 ***	0.8912 ***	0.8773 ***	0.9109 ***
LPATENT	-0.0589 ***	-0.0636 ***	-0.0695 ***	-0.0745 ***	-0.0783 ***	-0.0690 ***
LGDP	-1.005 ***	-0.9771 ***	-0.9416 ***	-0.9116 ***	-0.8885 ***	-0.9442 ***
LREN	-0.0928 ***	-0.0924 ***	-0.0919 ***	-0.0915 ***	-0.0912 ***	-0.09195 ***
LURB	-3.2976 ***	-3.2833 ***	-3.2650 ***	-3.2495 ***	-3.2377 ***	-3.2663 ***

Notes: *** denotes statistical significance at the (1%) level.

Table 10 above shows that all the variables are statistically significant at a (1%) level in all quantiles and OLS with fixed effects. Moreover, the results of the MM-QR indicate that the independent variable LCO_2 has a positive effect on the dependent variable (LOUT). This result means that CO_2 emissions increase premature deaths from outdoor air pollution. However, the independent variables LPATENT, LGDP, LREN, and LURB negatively affect the dependent variable (LOUT). The eco-innovation initiatives, GDP, renewable energy consumption, and urbanization mitigate premature deaths from outdoor pollution.

OLS with fixed effects results indicates that the independent variable LCO_2 has a positive effect of 0.9109 on the dependent variable (LOUT). However, the independent variables LPATENT, LGDP, LREN, and LURB have negative impacts of -0.0690, -0.9442, -0.09195, and -3.2663, respectively, on the dependent variable (LOUT). Indeed, the results of the OLS estimation confirm that the MM-QR is robust even with the change of method. Moreover, it is worth remembering that the OLS results with fixed effects are similar to those of the 50th quantile of the MM-QR (Koengkan et al., 2022). Indeed, **Figure 5** below summarizes the impact of independent variables on dependent ones indicated in **Table 10** above.

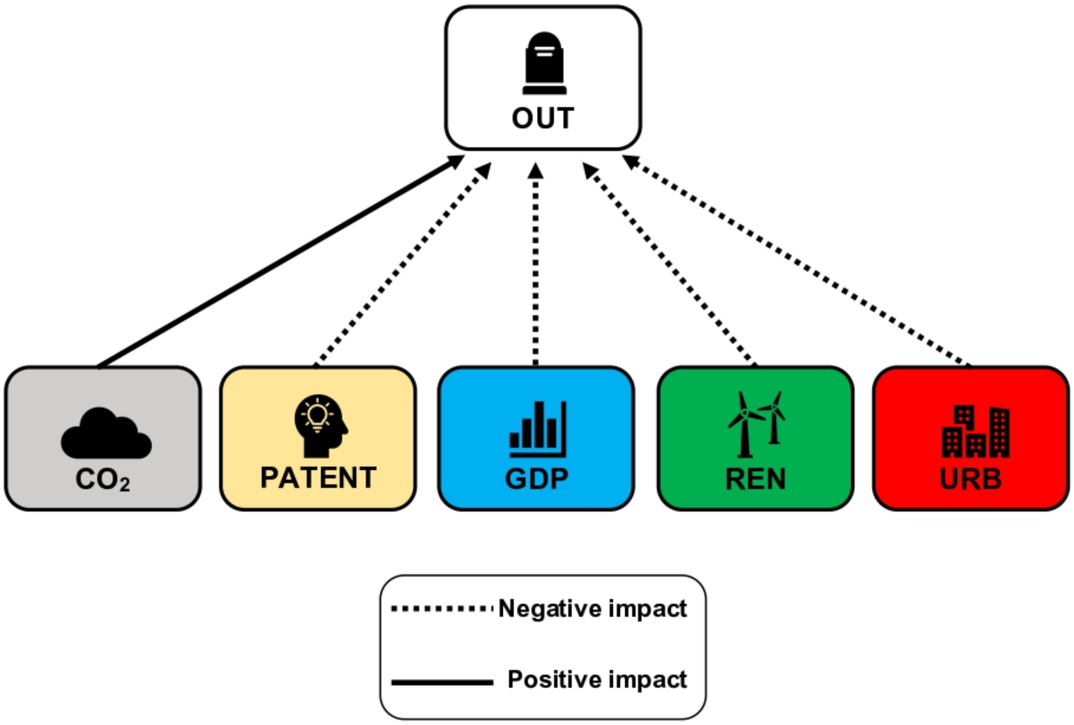

Figure 5. Summary of the variable's effect. The authors created this figure.

After realizing the econometric estimation of Model I, it was necessary to carry out the estimation of Model II, with LIND as the dependent variable. **Table 11** below shows OLS results with fixed effects and the MM-QR from Model II.

Table 11. Estimation results of the MM-QR regression model and OLS with fixed effects (**Model II**)

Independent variables	The main method: MM-QR, Model II-Dependent variable (LIND), Quantiles										Robustness check: OLS, Fixed Effects	
	10^{th}		25^{th}		50^{th}		75^{th}		90^{th}			
LCO_2	1.6317	***	1.5437	***	1.4185	***	1.2330	***	1.1165	***	1.3894	***
LPATENT	-0.0931	**	-0.1102	***	-0.1346	***	-0.1708	***	-0.1935	***	-0.1403	***
LGDP	-1.7150	***	-1.7392	***	-1.7737	***	-1.8249	***	-1.8570	***	-1.7818	***
LREN	-0.1777	***	-0.1741	***	-0.1689	***	-0.1612	***	-0.1564	***	-0.1677	***
LURB	-6.9617	***	-6.9962	***	-7.0453	***	-7.1180	***	-7.1636	***	-7.0567	***

Notes: *** and ** denote statistical significance at the (1%) and (5%) levels, respectively.

Table 11 above shows that all variables are statistically significant at a (1%) level in all quantiles and OLS with fixed effects. Moreover, the results of the MM-QR indicate that the independent variable LCO_2 positively impacts the dependent variable (LIND). Thus, CO_2 emissions increase premature deaths from outdoor air pollution. However, the independent variables LPATENT, LGDP, LREN, and LURB negatively affect the dependent variable (LIND). The eco-innovation initiatives, GDP, renewable energy consumption, and urbanization mitigate premature deaths from outdoor pollution.

OLS with fixed effects results reveals that the independent variable LCO_2 has a positive effect of 1.3894 on the dependent variable (LIND). However, the independent variables LPATENT, LGDP, LREN, and LURB have negative impacts of -0.1403, -1.7818, -0.1677, and -7.0567, respectively, on the dependent variable (LIND). **Figure 6** below summarizes the impact of independent variables on dependent ones indicated in **Table 11** above.

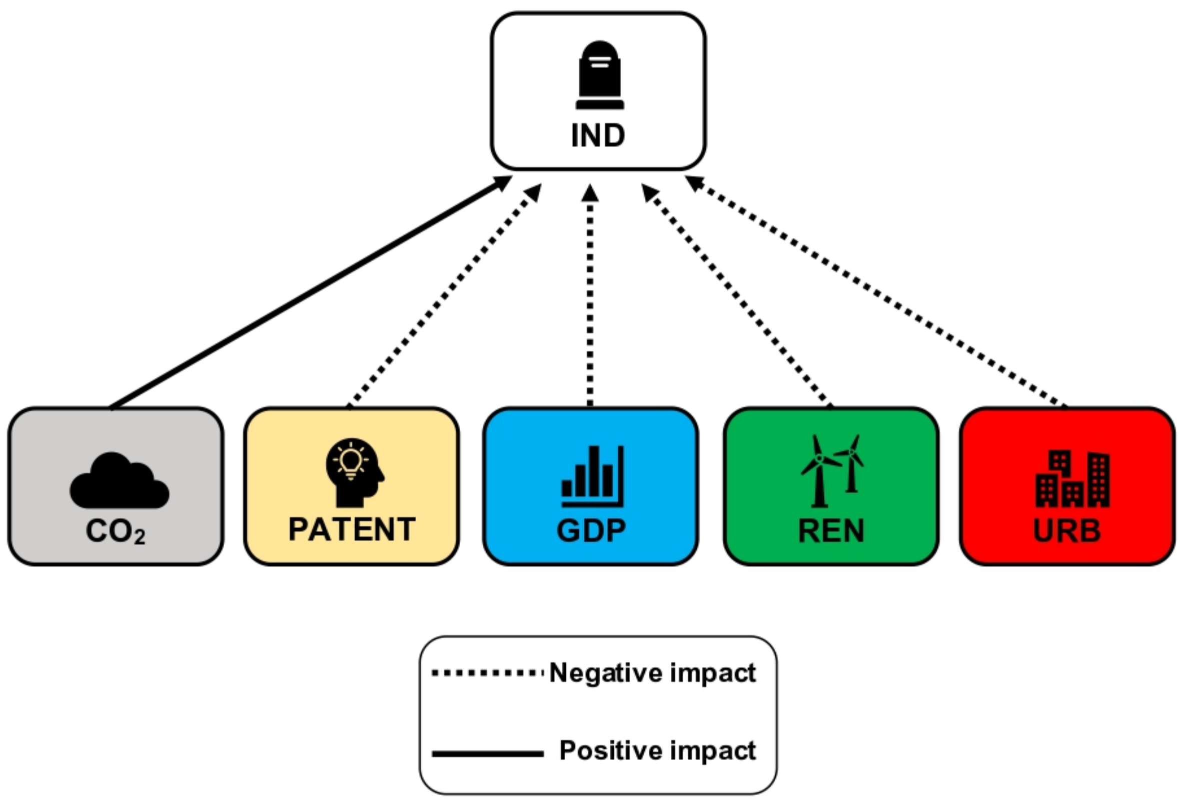

Figure 6. Summary of the variable's effect. The authors created this figure.

4.3. *Robustness check*

To check the model robustness in this research, we estimate both models (**Model I and Model II**) without the urbanization (**LURB**) variable (control variable). The robustness results of both models are given in **Table 12**. As can be seen, the results of both robustness models confirm the main models, and their signs and significance are the same.

Table 12. Robustness check results (**Model I and Model II**)

Independent variables	Model I-Dependent variable (LOUT)									
	Quantiles									
	10th		25th		50th		75th		90th	
LCO_2	1.2101	***	1.1730	***	1.1298	***	1.0886	***	1.0600	***
LPATENT	-0.0771	**	-0.0856	***	-0.0955	***	-0.1050	***	-0.1116	***
LGDP	-0.1045	***	-0.1015	***	-0.0979	***	-0.0946	***	-0.0922	***
LREN	-1.0757	***	-1.0672	***	-1.0574	***	-1.0481	***	-1.0416	***
Model II-Dependent variable (LIND)										
LCO_2	2.2320	***	2.1020	***	1.9070	***	1.6228	***	1.4715	***
LPATENT	-0.1202	**	-0.1472	***	-0.1876	***	-0.2465	***	-0.2779	***
LGDP	-0.1741	***	-0.1766	***	-0.1804	***	-0.1859	***	-0.1889	***
LREN	-1.8455	***	-1.9105	***	-2.007	***	-2.1499	***	-2.2255	***

Notes: *** and ** denotes statistical significance at the (1%) and (5%) levels, respectively.

We also applied the Dumitrescu-Hurlin (2012) panel causality test to check the causality between the variables. **Table 12** shows the Domitresco-Horlin panel causality test results for important variables.

Table 13. Pairwise Dumitrescu-Hurlin Panel causality test results

Null hypothesis:	W-Stat.	Zbar-Stat.	p-value	Results	Causality
$LCO_2 \nrightarrow LOUT$	3.0610***	7.8482	0.0000	Yes	↔
$LOUT \nrightarrow LCO_2$	4.6619***	13.9442	0.0000	Yes	
LPATENT ↛ LOUT	1.7163***	2.7274	0.0000	Yes	↔
LOUT ↛ LPATENT	2.2030***	4.5810	0.0000	Yes	
LREN ↛ LOUT	1.9961***	3.7932	0.0001	Yes	↔
LOUT ↛ LREN	5.3952***	16.7363	0.0000	Yes	
LGDP ↛ LOUT	0.1874**	2.5211	0.0117	Yes	↔
LOUT ↛ LGDP	2.0714***	4.0799	0.0000	Yes	
LURB ↛ LOUT	4.1080***	11.8349	0.0000	Yes	↔
LOUT ↛ LURB	11.6307***	40.4807	0.0000	Yes	
$LCO_2 \nrightarrow LIND$	7.4009***	24.3739	0.0000	Yes	↔
$LIND \nrightarrow LCO_2$	5.6267***	17.6180	0.0000	Yes	
LPATENT ↛ LIND	2.2201***	4.6459	0.0000	Yes	↔
LIND ↛ LPATENT	2.6532***	6.2950	0.0000	Yes	
LREN ↛ LIND	2.9672***	7.4909	0.0000	Yes	↔
LIND ↛ LREN	5.0428***	15.3945	0.0000	Yes	
LGDP ↛ LIND	4.6822	14.0216	0.0000	Yes	↔
LIND ↛ LGDP	1.6431**	2.4489	0.0143	Yes	
LURB ↛ LIND	10.2332***	35.1590	0.0000	Yes	↔
LIND ↛ LURB	17.7350**	63.7250	0.0000	Yes	

Note: *, ** and *** indicates (10%), (5%), and (1%) significance levels, respectively; double-side arrows show bi-direction; a single arrow shows unidirectional and ↛ shows no causality.

As can be seen, in Model I (lout), all variables include CO_2 emissions (LCO_2), economic growth (LGDP), environmental innovation (LPATENT), renewable energy consumption (LREN), and urbanization (LURB), a bidirectional causal relationship with outdoor air pollution death (LOUT). Indeed, **Figure 7** below summarizes the causality between independent variables with dependent ones found in **Table 13** above.

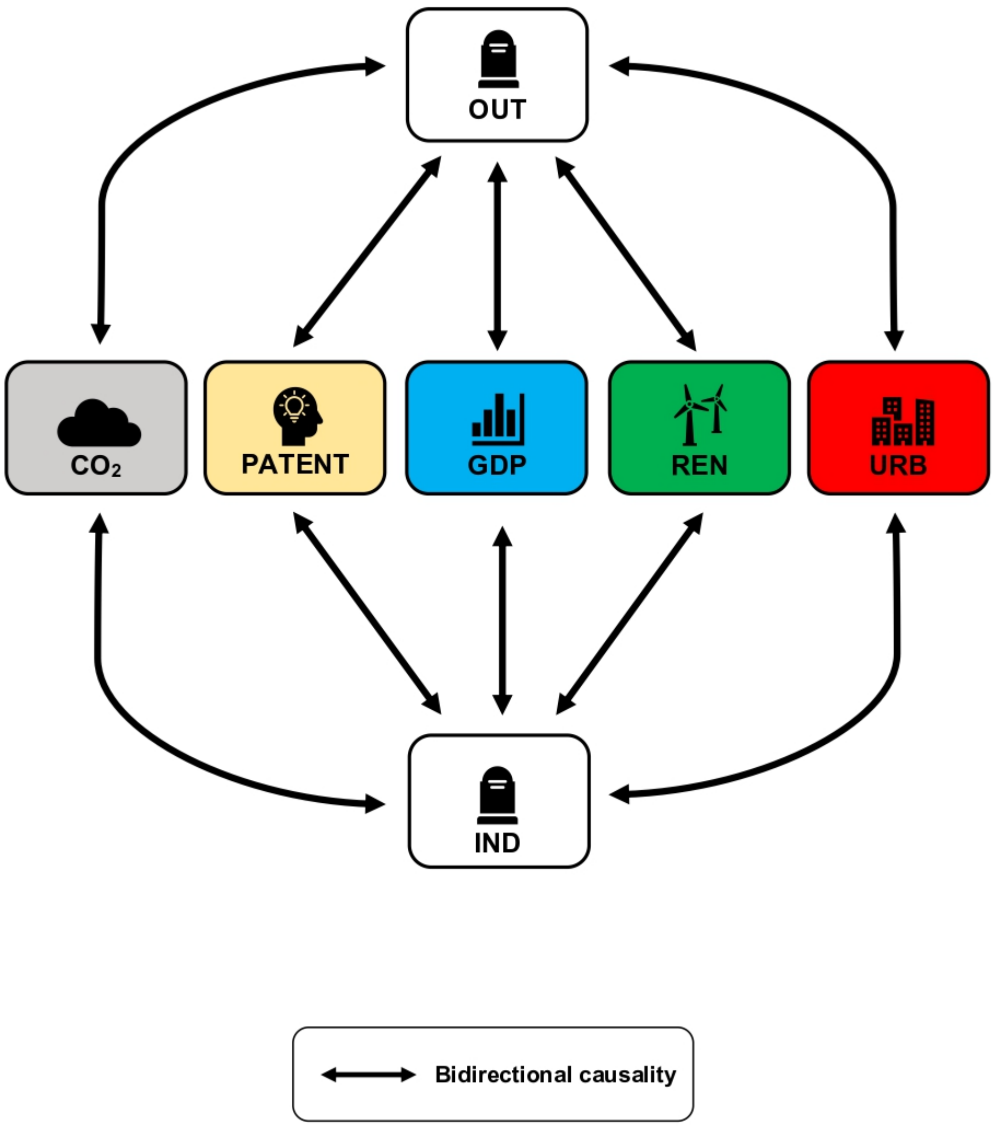

Figure 7. Summary of the variables' causality. The authors created this figure.

The results of the causal relationship for Model II (LIND) also confirm the two-way causal relationship between indoor air pollution death (LIND) and all variables affecting it. In addition, these results confirmed the robustness of both models.

5. Discussion

This section is devoted to the explanation of the obtained results. The positive impact of the independent variable LCO_2 on the dependent variables LOUT and LIND was found by Koengkan et al. (2021) and Jacobson (2008). According to the authors, CO_2 emissions originating from the combustion processes of solid fuel burning, industry, and motor vehicles are significant air pollutants that cause premature deaths. This result means that the CO_2 emissions are directly related to premature deaths from air pollution. For this reason, their signal is positive in this investigation.

Given that increased economic growth leads to more CO_2 emissions. Therefore, countries with higher CO_2 emissions are usually associated with high income per capita levels and elevated levels of industrialisation. According to Jaunky (2011), in the rich and industrialised countries, the increase of (1%) in GDP generates an increase of (0.68%) in CO_2 emissions in the short run and (0.22%) in the long run. Furthermore, high income per capita levels increase public investment in the health sector, provide health facilities, and improve the health system, which can help reduce mortality from air pollution, as Koengkan et al. (2022) and Koengkan et al. (2021) found.

Moreover, another possible explanation could be related to the increase in air pollution or CO_2 emissions in some European countries. This possible increase could be related to some European countries being dependent on fossil fuels to grow or having high participation of fossil fuels in their energy matrix. However, several decarbonization initiatives have been implemented in the last decades to reduce the consumption of fossil fuels (Fuinhas et al., 2021). According to Europa (2022b), in 2019, the energy mix in the EU countries was composed of natural gas (22%), nuclear energy and solid fossil fuels (both 13%), petroleum products (including crude oil) (36%), and renewable energy (15%).

Indeed, the shares of diverse energy sources in the total available energy considerably vary in the EU countries. For example, a significant share of total energy available in Malta (87%), Cyprus (90%), and Luxembourg (65%) belongs to petroleum products (including crude oil). Also, natural gas generates over one-third of the total energy in the Netherlands (37%) and Italy (39%). Moreover, solid fossil fuels account for more than half of the energy available in Estonia (60%) and (43%) of the total energy in Poland. On the other hand, nuclear energy accounts for (31%) of the total energy in Sweden and (41%) in France. Finally, renewable energy constitutes (37%) of the available energy in Latvia and (41%) in Sweden (Europa 2022b).

As mentioned in the introduction, the impact of eco-innovative initiatives on premature deaths from air pollution has never been approached. As a result, our investigation opted to use studies close to this topic of investigation to explain the negative impact of the independent variable LPATENT on the dependent variables LOUT and LIND. Therefore, the negative impact caused by the independent variable LPATENT could be related to the capacity of eco-innovative initiatives to mitigate CO_2 emissions in the European countries.

In the literature, the evidence that eco-innovative initiatives can reduce environmental degradation has been confirmed by several authors (for example, Alam et al., 2021; Cheng et al., 2021; Ahmad et al., 2021; Meirun et al., 2021; Hasanov et al., 2021; Abid et al., 2021; Dauda et al., 2021; Chen and Lee, 2020; Wang and Zhu, 2020; Khattak et al., 2020; Koçak and Ulucak, 2019; Petrović and Lobanov, 2019; Hashmi and Alam, 2019; Cheng et al., 2019a; Cheng et al., 2019b; Du et al., 2019; Ganda, 2019; Dauda et al., 2019; and Fernández et al., 2018). In a study for the G7, Qin et al. (2021) confirmed the role of environmental technologies in controlling CO_2 emissions. On the other hand, Sun et al. (2022) for top-10 polluted countries found that environmental innovations can reduce CO_2 emissions only in the middle and upper quantiles. In a study for China, Guo et al. (2021) found that investing in green technology can help reduce CO_2 emissions. Indeed, most of these authors explain that investments in eco-innovative initiatives, such as patents of renewable energy technologies and technologies that consume less energy, reduce the consumption of non-renewable sources of energy and, accordingly, CO_2 emissions. Moreover, this negative impact also could be related to the boom in the green industries in the EU. According to Europa (2022a), from 2000 to 2011, the environment industry grew by more than fifty per cent in the EU. In the EU, more than three million people are employed by eco-industries. Also, European businesses supply one-third of the global green technologies market, a market worth €1 trillion, which is expected to double in five years.

The negative impact of the independent variable LGDP on the dependent variables LOUT and LIND was found by Koengkan et al. (2022). According to the authors, this negative impact is related to the modernization of industries and infrastructures via green energy technologies that consume less energy. The income increase allows the industries, government, and households vast access to green energy technologies and technologies that consume less energy or resources. Indeed, this would be possible only through heavy investments in R&D, eco-innovative initiatives, and the trade and financial liberalization caused by economic development. Furthermore, the negative impact of the variable LGDP could result from the boom in the green industries in the EU, as mentioned before, where the EU countries have massively invested in initiatives to decarbonize their economies.

Another possible explanation is related to substantial investments in the health sector in the EU countries in the last decades. The average ratio of health spending to GDP across the EU countries sharply jumped from (3.8%) in 2005 to (8.5%) in 2009 (OECD, 2020). Therefore, the mortality caused by air pollution could be reduced by increasing health spending in EU countries.

The negative impact of the independent variable LREN on the dependent variables LOUT and LIND was found by Koengkan et al. (2022) and Koengkan et al. (2021). According to the authors, this negative impact is related to the capacity of renewable energy consumption to mitigate air pollution. The same authors state that this reduction is possible because of the existence of efficiency policies that encourage developing, producing, and consuming green energy technologies. Moreover, this negative impact could be related to the increase in the share of renewable energy in European countries. While the few investigations mentioned earlier examined the effects of renewable energy consumption on mortality from air pollution, several studies confirmed the effect of renewable energy consumption on reducing CO_2 emissions (for example, Adebayo et al., 2022; Khattak et al., 2020; Haldar et al., 2021; Mehmood, 2022; Akram et al., 2020; Saidi et al., 2020). Therefore, reducing CO_2 emissions also decreases mortality from air pollution.

Finally, the negative impact of the independent variable LURB on the dependent variables LOUT and LIND could be related to two factors, as mentioned by Koengkan and Fuinhas (2021). The first factor is reducing the urban population, which affects energy consumption from households, industries, the transport sector, and, accordingly, the CO_2 emissions. Second, it could be a result of (a) the consideration of diverse sources of energy and renewable sources in the energy matrix in large urban centres; (b) the improvement of energy efficiency as a result of the introduction and development of new energy technologies; and (c) the introduction of environmental regulations to encourage families and industries for the acquisition of technologies that restrict the use of cars utilizing fossil fuels and are environment-friendly, as occurred in some large cities in Europe. Furthermore, individual transport can be reduced by investing in public transport based on alternative energy sources.

6. Policy implications and conclusions

The main question of this research can be stated as follows. Do environmental innovations play an essential role in the reduction of air pollution? A positive answer to this question will help the reduction of pollution-related deaths and represent one more benefit of the challenging transition to a sustainable world.

To assess the validity of the relationship, the effect of eco-innovations on premature deaths resulting from indoor and outdoor air pollution was examined in twenty-nine European countries from 1995 to 2019. The moments' quantile regression (MM-QR) method was the most suitable econometric technique to perform the empirical analysis. Two models were developed to assess the relationship. The first model explained the effects of CO_2 emissions, patents on environmental technologies, GDP, renewable energy consumption, and the percentage of urban population on the rates of deaths resulting from outdoor air pollution. The second model explored the effects of the same explanatory variables present in the previous model but on the rates of deaths resulting from indoor air pollution.

The most important result of this research was the confirmation of heterogeneous effects of the main variables in both models. Indeed, both models indicated that eco-innovations reduced premature deaths from outdoor and indoor air pollution. However, these effects were more extensive in upper quantities (75th and 90th). Also, it was found that the effect of eco-innovations on reducing mortality due to indoor pollution was more pronounced than the one due to outdoor pollution. Moreover, eco-innovation, economic growth, renewable energy consumption, and urbanization reduced premature mortality due to indoor and outdoor air pollution. Conversely, CO_2 emissions increased premature mortality.

Our study filled the gap in the literature concerning the association between eco-innovation initiatives and the reduction of premature deaths attributed to outdoor and indoor air pollution. Indeed, the contribution to literature was threefold (i) through its innovative addressing of the effect of eco-innovation initiatives on premature deaths resulting from outdoor and indoor air pollution by studying a representative group of European countries, (ii) by the introduction of novel econometric models to the topic under consideration, and (iii) by supporting policymakers in developing initiatives promoting the development of eco-innovative solutions to improve the environment.

Assess the indirect effects (the ones the project's promotors cannot capture) are a crucial part of fighting the adverse effects of environmental damage. Moreover, innovation requires substantial financial resources. Consequently, economists are expected to assess if their uses can alleviate humankind's problems. However, here we have focused only on one dimension of innovation, the patents on environmental technologies, and evaluate if this eco-innovation can mitigate one of the vast environmental problems, i.e., the deaths from inside and outside pollution. Furthermore, suppose these environmental technologies reveal positive indirect effects on public health. In that case, their benefits increase compared to the financial cost of their research and development. This result is what our research revealed. Therefore, when policymakers support the financing of eco-innovation, society gets more than what is captured by looking at its financial returns.

Policymakers must incentivize innovation's significant economic and social behaviour effects to reduce premature deaths. As this study proved, CO_2 emissions should be curbed by encouraging the adoption of electric vehicles using electricity generated from renewable energy sources. Interventions in the industry to promote energy efficiency, filter pollution, and store carbon emissions are also advised. On the other hand, research should be financed to increase patents on environmental technologies. The available innovations can accelerate the modernization of industries and infrastructures by deploying green-energy and energy-saving technologies. The substitution of fossil energy with renewable sources should be accelerated to reduce CO_2 emissions. Also, investment in public transportation should be increased to take advantage of urbanization and achieve more efficiency in transportation. Finally, environmental regulations should encourage industries' and households' acquisition of environment-friendly technologies.

As this research proved, the impact of eco-innovative initiatives on premature deaths from air pollution is real. Consequently, policymakers must promote eco-innovations with a substantial impact on the environment.

Author Contributions Matheus Koengkan: conceptualization, writing-original draft, validation, data curation, investigation, formal analysis, and visualization; Emad Kazemzadeh: writing-original draft and editing, supervision, validation, data curation, and project administration; José Alberto Fuinhas: editing, supervision, writing-original draft, investigation, and funding acquisition; Mohammad Nabi Shahiki Tash: writing, validation, and editing. All authors have read and agreed to the published version of the manuscript.

Data availability Corresponding authors can provide the data used in the study on appropriate requests.

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Declarations

Ethical approval Authors are attested that this paper has not been published elsewhere, the work has not been submitted simultaneously for publication elsewhere, and the results presented in this work are true and not manipulated.

Competing interests The authors declare no competing interests

Consent to participate Not applicable.

Consent for publication Not applicable.

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