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NON-RENEWABLE AND RENEWABLE ENERGY CONSUMPTION AND CO_2 EMISSIONS IN OECD COUNTRIES: A COMPARATIVE ANALYSIS

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Abstract

This paper attempts to explore the determinants of CO_2 emissions using the STIRPAT model and data from 1980 to 2011 for OECD countries. The empirical results show that non-renewable energy consumption increases CO_2 emissions, whereas renewable energy consumption decreases CO_2 emissions. Further, the results support the existence of an Environmental Kuznets Curve between urbanisation and CO_2 emissions, implying that at higher levels of urbanisation, the environmental impact decreases. Therefore, the overall evidence suggests that policy makers should focus on urban planning as well as clean energy development to make substantial contributions to both reducing non-renewable energy use and mitigating climate change.

Keywords: Renewable energy consumption, Non-renewable energy consumption, CO_2 emissions, Urbanisation, STIRPAT model

JEL classification: C23, C33, Q21, Q43, Q48

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1. Introduction

The OECD countries enjoy energy-led growth and remain the largest energy consuming countries with 41% of the total global energy consumption (Duffour, 2012). Major portion of this energy supply comes from conventional non-renewable sources such as coal, oil and natural gas. As a result, there is a sharp increase in carbon dioxide (CO_2) emission in the atmosphere which is considered to be the main source of greenhouse gas (GHG) effect that led to environmental degradation. Thus, the climate change intimidation and the increasing threat of global warming raise worldwide concerns and impose serious social and political pressure to curb emissions. Most OECD countries signed Kyoto Protocol to reduce their overall greenhouse gas emissions by an average of at least 5.2 % below their 1990 levels in the five years after 2008. Therefore, to combat climate change and to secure & diversify the supply of energy mix there has been heightened interest in renewable energy sources in OECD countries in recent years. This growing interest has been supported by various government incentive policies such as feed-in tariff, subsidies for renewable technologies, tax rebate and so on. As a result, the share of renewables in total power generation exceeds 20 per cent in OECD countries in 2011 (Duffour, 2012). Hence, identifying the relationship between renewable and non-renewable energy consumption and pollutant emission is worth academic investigation.

Human activities involving the combustion of fossil fuels and the burning of biomass, produce GHGs that affect the composition of the atmosphere and the global climate (IPCC 2001). These activities constantly increase with the rapid pace of industrialisation and urbanisation in recent decades, which ultimately cause serious damage to environment through energy consumption. In addition, expansion in service industries, which is the result of economic development, can increase energy demand and consequently leads to pollutant emissions. Therefore, the aim of this article is to identify the determinants of pollutant emission by using a statistical model, namely STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) using data over the period of 1980-2011 from the OECD countries.

Numerous studies have dealt with the relationship between energy consumption and pollutant emissions. These studies have been performed in different countries and with various modelling methods, approaches and findings. However, only a few studies have investigated the relationship between disaggregated energy consumption and CO_2 emissions. No consensus has emerged from these studies. Therefore, the focus of this article is to contribute further to this literature by using disaggregated energy consumption (renewable and non-renewable) and comparing the effects of renewable and non-renewable energy consumption on CO_2 emissions. To the best of authors' knowledge, this is one of the first studies to simultaneously investigate the effects of renewable and non-renewable energy consumption on CO_2 emissions using the STIRPAT model. Additionally, this article also investigates the relationship between urbanisation and CO_2 emissions by emphasising the Environmental Kuznets Curve (EKC) hypothesis.

The rest of the article is organised as follows: Section 2 provides a critical review of the existing literature. Section 3 presents the research methodology, including model specification and the estimation strategy. The empirical results are reported in Section 4. Finally, Section 5 concludes the article.

2. A Critical Review of the Literature

2.1 Renewable Energy Consumption, Economic Growth and CO_2 Emissions

The relationships between economic growth and pollutant emissions and between economic growth and energy consumption, in addition to the combination of these two nexuses in a single framework, have been investigated extensively. However, limited research has been conducted on the nexus between renewable energy sources, economic growth and pollutant emissions.

Sadorsky (2009) finds that in the long run, real GDP per capita and the CO_2 emissions per capita had positive effects on renewable energy consumption in the G7 countries from 1980 to 2005. Apergis et al. (2010) demonstrate that in the short run, nuclear energy consumption reduces CO_2 emissions, whereas renewable energy consumption does not contribute to reductions in emissions. These authors note that the latter result may be due to the limited proportion of renewable energy in total energy consumption. In the case of the US, Menyah and Wolde-Rufael (2010) find that although there was no causality from renewable energy consumption to CO_2 emissions, there was unidirectional causality from CO_2 emissions to renewable energy consumption over the period from 1960 to 2007. Salim and Rafiq (2012) investigate the relationship between CO_2 emissions and renewable energy consumption, controlling for income and oil prices. The long-run results obtained using the dynamic OLS and fully modified OLS methods show that CO_2 and income are the major determinants of renewable energy consumption in Brazil, China, India and Indonesia. For these countries, a bidirectional causal relationship is also found between renewable energy consumption and CO_2 emissions in the short run. The results also indicate that there is bidirectional relationship between income and CO_2 emissions in Brazil, China and Turkey. Using the Toda-Yamamoto procedure over the period from 1949 to 2009 for the US, Payne (2012) reveals that real GDP and CO_2 emissions do not have causal effects on renewable energy consumption. However, unexpected shocks to real GDP and CO_2 emissions positively affect renewable energy consumption over time.

2.2 Review of Empirical Works Based on the STIRPAT Model

The STIRPAT method has been applied by several scientists to investigate the effects of driving forces on pollutant emissions. For instance, York et al. (2003a) study a non-linear relationship between emissions and factors such as population, urbanisation and economic growth for 142 nations and find a positive relationship between emissions and the independent variables. In a similar study, York et al. (2003b) conclude that the elasticity of CO_2 emissions with respect to population is close to unity. Shi (2003) finds a direct relationship between population changes and emissions in 93 countries over the period from 1975 to 1996. Using a sample of 86 countries during the period from 1971 to 1998, Cole and Neumayer (2004) study the effects of population size and several other demographic factors, including age composition, the urbanisation rate and the average household size, on CO_2 and sulphur dioxide (SO_2) emissions. The results indicate that there is a U-shaped association between population size and SO_2 and a positive association between the urbanisation rate and CO_2 emissions. Moreover, a higher average household size is found to decrease emissions. In contrast, a negative relationship between urbanisation and CO_2 emissions is found by Fan et al. (2006) for developed countries over the period 1975 to 2000. The same result is obtained by Martínez-Zarzoso et al. (2007). These authors analyse the determinants of CO_2 emissions during the period of 1975 to

2003 and demonstrate that although the elasticity of emission-urbanisation is positive in low-income countries, it is negative in middle upper and high income countries.

Lin et al. (2009) add urbanisation and industrialisation factors to the basic model and name the new model STIRPUrlnAT. These authors use this revised model to analyse environmental impacts in China from 1978 to 2006 and find that the population had the largest potential effect on environmental impact, followed by the urbanisation level, the industrialisation level, GDP per capita and the energy intensity. Similar to the study of Fan et al. (2006), a study by Poumanyvong and Kaneko (2010) considers different development stages and provides evidence of positive effects of population, affluence and urbanisation on CO_2 emissions for all income groups, low, middle and high. Considering aggregate CO_2 emissions and CO_2 emissions from transport for 17 developed countries covering the period from 1960 to 2005, Liddle and Lung (2010) reveal that the total population and economic growth positively influence these two types of emissions. However, urbanisation has a positive and significant impact on only CO_2 emissions from transport. When improving this study by performing unit root and cointegration tests, Liddle (2011) finds positive associations between GDP per capita and CO_2 emissions from transport and between the total population and CO_2 from transport. Using a panel of 29 provinces in China from 1995 to 2010, Zhang and Lin (2012) show that population, affluence, industrialisation and energy intensity increase CO_2 emissions for the whole sample, whereas the results are different across the different regions.

2.3 CO_2 Emissions, Urbanisation and Income: The Environmental Kuznets Curve (EKC) Hypothesis

Empirical studies related to the link between environmental degradation and economic activities usually refer to the Environmental Kuznets Curve (EKC) hypothesis, which suggests that there is an inverted U-shaped relationship between pollutant emissions and income per capita. A large number of studies have tested the economic growth and environmental pollution nexus (Selden and Song 1994; Grossman and Krueger 1995; Galeotti and Lanza 1999; Halicioglu 2009; Kearsley and Riddel 2010 and so on). Some of these studies have focused on developed countries. For instance, Dijkgraaf and Vollebergh (2001) find a statistically significant turning point and confirm the inverted U EKC pattern for 11 out of 24 OECD countries. Martínez-Zarzoso and Bengochea-Morancho (2004) analyse 22 OECD countries using a pooled mean group estimator and provide evidence of an N-shaped relationship for the majority of these countries. In contrast, Liu (2005) studies 24 OECD nations using panel data and finds that the EKC exists for CO_2 emissions. Similarly, the evidence supporting the EKC is found by Galeotti et al. (2006) for the OECD countries from 1950 to 1998. Canas et al. (2003) also find an inverted U-shaped EKC relationship for 16 industrialised countries for the period from 1960 to 1998.

Considering nuclear power generation, Richmond and Kaufman (2006) investigate the EKC for CO_2 using panel data for OECD countries and note that there is limited support for the EKC in the case of OECD countries. Iwata et al. (2010) also take into account nuclear energy and find poor evidence in support of the EKC hypothesis in the cases of 11 OECD countries.

Recently, a few studies have examined the EKC hypothesis in terms of the relationship between pollutant emissions and urbanisation. For instance, York et al. (2003b) find that there is no evidence of the EKC for total CO_2 emissions and urbanisation in 142 nations in the year 1996. For developing countries during the period from 1975 to 2003, Martínez-Zarzoso and Maruotti (2011) confirm the existence of an inverted U-shaped relationship between CO_2 emissions and urbanisation, indicating that urbanisation at higher levels contributes to reductions in environmental damage. Using a semi-parametric model, Zhu et al. (2012) find little evidence in support of an inverted U-shaped relationship between CO_2 emissions and urbanisation in a sample of 20 emerging countries over the period from 1992 to 2008.

The general observation from the literature is that although the relationships between energy consumption, emissions and economic growth are widely discussed, the results are still inconclusive. Most studies are criticised regarding the validity of the estimated coefficients and their elasticities because the tests used are not based on an appropriate quantitative framework. For example, studies fail to take into account the diagnostic statistics and specification tests that are necessary to obtain unbiased and consistent regression results.

This article differs from the existing studies in a number of ways. First, it estimates the long-run and short-run impacts of both renewable and non-renewable energy consumption on CO_2 emissions simultaneously. Second, it investigates the relationship between CO_2 emissions and urbanisation using the EKC hypothesis, an analysis that has not been previously performed for the OECD countries. Third, this study controls for the results of the diagnostic and specification tests, which have been seldom considered in previous works. Finally, it makes use of recent panel data techniques that allow the analysis of heterogeneous unobserved parameters and cross-sectional dependence.

3. Research Method

3.1 Model Specification

The IPAT identity is a widely recognised formula for analysing the effects of human activities on the environment (Stern et al. 1992; Harrison and Pearce 2000). Ehrlich and Holdren (1971) and Holdren and Ehrlich (1974) introduced the IPAT identity based on the principal driving forces of anthropogenic environmental impacts in the early 1970s. It has been widely utilised as a framework for analysing the driving forces of environmental change (Raskin 1995; York et al. 2002). The IPAT identity specifies that environmental impacts (*I*) are the multiplicative product of three key driving forces: population (*P*), affluence (*A*) (per capita consumption or production) and technology (*T*) (impact per unit of consumption or production); hence, I = PAT (Ehrlich and Holdren 1971; Ehrlich and Ehrlich 1990; Raskin 1995; York et al. 2003b). The strengths of the IPAT identity are that it specifies key driving forces behind environmental change with parsimony, and further, it defines mathematically the relationship between the driving forces and impacts (Dietz and Rosa 1997, York et al. 2003b).

Waggoner and Ausubel (2002) introduce another approach based on the IPAT identity, namely ImPACT. In the ImPACT model, *T* is disaggregated into consumption per unit of GDP (*C*) and impact per unit of consumption (*T*) so that I = PACT. Another extension of IPAT has been suggested by Schulze (2002), who added the factor behaviour (B) to this identity, giving I = PBAT. However, Diesendorf (2002) and Roca (2002) note that behaviour is already included in each factor in the right-hand side of the equation of I = PAT. In addition, behaviour is not an easily measurable quantity.

Despite the fact that IPAT and ImPACT are parsimonious and flexible and easily indicate the effects of driving forces on environmental conditions, they suffer from several limitations. IPAT and ImPACT assume proportionality between the key determinant factors, meaning that when changing one factor, the others should be held constant. Furthermore, these models do not allow for non-monotonic or non-proportional effects of the driving forces (York et al. 2003b).

To overcome these limitations, Dietz and Rosa (1994, 1997) present a new model, STIRPAT (STochastic Impacts by Regression on Population, Affluence, and Technology). This model is no longer an accounting equation, and therefore, it can be used to test hypotheses empirically. STIRPAT has the following basic form:

$$I_i = \alpha P_i^b A_i^c T_i^d e_i \tag{1}$$

Taking the natural logarithm of both sides:

$$\ln I_{it} = \ln \alpha + b \ln(P_{it}) + c \ln(A_{it}) + d \ln(T_{it}) + \ln e_{it} \tag{2}$$

where α represents a constant; b, c and d are the exponents of P, A and T, which indicate, respectively, the effects of population elasticity, affluence elasticity and technology elasticity; e is the error term; and t denotes the year. The subscript i illustrates the differences between the quantities I, P, A, T and e across observational units.

In this paper, three different models are used to estimate the effects of different variables on CO_2 emissions. In the first model (Model I), the relationship between CO_2 emissions and renewable and non-renewable energy consumption is investigated. According to York et al. (2003b), additional factors can be entered into the basic STIRPAT model as components of the technology term (T). Because T is basically considered to be the environmental impact per unit of economic activity, in this study, T is disaggregated into two factors that denote the difference in the economic structure of each country in terms of the type of energy used: renewable energy and non-renewable energy. Therefore, T represents renewable energy use and non-renewable energy use as follows:

$$\ln(CO_{2it}) = \ln \alpha_0 + \alpha_1 \ln(P_{it}) + \alpha_2 \ln(A_{it}) + \alpha_3 \ln(R_{it}) + \alpha_4 \ln(N_{it}) + \ln e_{1it} \tag{3}$$

where P, A, R and N denote the total population size, GDP per capita, renewable energy consumption and non-renewable energy consumption, respectively. e is the error term. The subscript i refers to countries, and t denotes the year.

In the second model (Model II), the effects of the total population, GDP per capita, industrialisation, the contribution of the service sector to GDP, population density and urbanisation are examined. Thus, the second model is given by:

$$\ln(CO_{2it}) = \ln b_0 + b_1 \ln(P_{it}) + b_2 \ln(A_{it}) + b_3 \ln(IND_{it}) + b_4 \ln(S_{it}) + b_5 \ln(U_{it}) + b_6 \ln(PD_{it}) + \ln e_{2it} \tag{4}$$

In this equation, P is the total population size, A is GDP per capita, IND is the contribution of the industry sector to GDP (industrialisation), S is the contribution of the service sector to GDP, PD is the population density and U is urbanisation.

The purpose of the third model (Model III) is to examine the relationship between CO_2 emissions, urbanisation and income using the EKC hypothesis. Following Martínez-Zarzoso and Maruotti (2011), the squared terms of affluence and urbanisation are added to the basic STIRPAT model, and energy intensity is used as a proxy for technology (T). The model is as follows:

$$\ln(CO_{2it}) = \ln c_0 + c_1 \ln(P_{it}) + c_2 \ln(A_{it}) + c_3 \ln(A_{it}^2) + c_4 \ln(U_{it}) + c_5 \ln(U_{it}^2) + c_6 \ln(EI_{it}) + \ln e_{3it} \tag{5}$$

In the above equation, P is the total population size, A is GDP per capita, A^2 denotes the squared term of GDP per capita, U is urbanisation, U^2 denotes the squared term of urbanisation and EI is the energy intensity.

3.2 Causality Analysis

Next, the Generalised Method of Moments (GMM) method is employed to examine the long-run and short-run Granger causalities between CO_2 emissions total population, population density, GDP per capita, urbanisation, industrialisation, the contribution of services to GDP and renewable and non-renewable energy consumption. The residuals, obtained using the long-run estimates in Model I and Model II, are used as dynamic error correction terms. The causality relationship between the variables is tested based on the following equations, considering each variable in turn as a dependent variable for each model.

$$\Delta LCO_{2it} = f_0 + \sum_{j=1}^{m} \delta_{11ij} \Delta LP_{it-j} + \sum_{j=1}^{m} \delta_{12ij} \Delta LA_{it-j} + \sum_{j=1}^{m} \delta_{13ij} \Delta LR_{it-j} + \sum_{j=1}^{m} \delta_{13ij} \Delta LN_{it-j} + \lambda_{it} e_{it-1} + u_{1it} \tag{6}$$

$$\Delta LCO_{2it} = g_0 + \sum_{j=1}^{m} \rho_{11ij} \Delta LP_{it-j} + \sum_{j=1}^{m} \rho_{12ij} \Delta LA_{it-j} + \sum_{j=1}^{m} \rho_{13ij} \Delta LIND_{it-j} + \sum_{j=1}^{m} \rho_{14ij} \Delta LS_{it-j} + \sum_{j=1}^{m} \rho_{15ij} \Delta LU_{it-j} + \sum_{j=1}^{m} \rho_{16ij} \Delta LPD_{it-j} + \lambda_{it} e_{it-1} + u_{1it} \tag{7}$$

In the above equations, CO_2 is total carbon dioxide, *N* is non-renewable energy consumption, *R* is renewable energy consumption, *P* is the total population size, *A* is GDP per capita, *IND* is the contribution of the industry sector to GDP, *S* is the contribution of the service sector to GDP, *PD* is the population density and *U* is urbanisation. The next section presents the estimation of the long-run panel elasticities of CO_2 emissions and identifies dynamic causal relationships between the variables. For this purpose, the results of the unit root and cointegration tests are provided.

3.3 *Data Description*

Annual data for a set of 29 OECD countries [1] covering the period from 1980 to 2011 are collected for CO_2 emissions, renewable energy consumption, non-renewable energy consumption, GDP per capita, urbanisation, total population size, industrialisation, the contribution of the service sector to GDP and population density. CO_2 refers to total carbon dioxide emissions that come from the consumption of energy in millions of metric tons. Energy intensity is measured as the total primary energy consumption in quadrillion Btu divided by GDP (year 2005 U.S. Dollars, Purchasing Power Parities). According to the Energy Information Administration (EIA), non-renewable energy sources include coal and coal products, oil and natural gas. Therefore, in this study, non-renewable energy consumption is measured as the aggregate of the consumption of all these sources in quadrillion Btu. Renewable energy consumption, in quadrillion Btu, includes the consumption of energy from wood, waste, geothermal sources, wind, photovoltaic cells and solar thermal sources.

[1] The 29 sample countries are Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Japan, South Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States.

The data for CO_2 emissions, energy intensity and renewable and non-renewable energy are sourced from the U.S. Energy Information Administration.

The total population is taken to be the midyear population size, and GDP per capita (US$ in PPP, year 2000 prices) is the gross domestic product divided by the midyear population. Urbanisation is generally measured as the percentage of the population living in urban areas. Therefore, the urban population (% of the total) is applied as a reliable proxy for urbanisation. The measure of industrialisation is constructed as the value of the gross domestic production created in the industrial sector, that is, industrial value added as % of GDP is considered here as a proxy for industrialisation. Industrial value added comprises value added by mining, manufacturing (also reported as a separate subgroup), construction, electricity, water and gas. Service sector value added, as a percentage of GDP, is considered a proxy for the contribution of the service sector to GDP. Services include wholesale and retail trade (including hotels and restaurants), transport and government, financial, professional and personal services such as education, health care and real estate services. Also included are imputed bank service charges, import duties and any statistical discrepancies noted by national compilers as well as discrepancies arising from rescaling. According to World Development Indicators, the population density is defined as the number of people living per square kilometre of land area. All the data are sourced from the World Bank's World Development Indicators. All variables are converted into natural logarithms prior to conducting the analysis.

3.4 Estimation Strategy

To explore the dynamics of the relationships between both energy and demographic and economic factors and CO_2 emissions, the following steps are performed. First, the existence of a unit root in each variable is tested. Then, if the variables contain unit roots, the long-run cointegration relationship between the variables in each model is examined. If the variables are cointegrated, the final step is to detect the direction of causality between the variables by applying the panel vector error correction model.

Before selecting an appropriate estimator to examine the long-run estimates of CO_2 emissions, it is important to perform diagnostic tests, including the cross-sectional dependence, heteroskedasticity and serial correlation tests. The results for all three models indicate the existence of cross-sectional dependence, heteroskedasticity and serial correlation among the variables in the three models. [2] To address this issue, a recently developed approach, the Augmented Mean Group (AMG) estimator developed by Eberhardt and Teal (2011), is applied. This estimator accounts for the effects of common shocks by including a "common dynamic process".

4. Empirical Analysis and Results

4.1 Panel Unit Root and Cointegration Tests

The results of the unit root test without structural breaks for the variables are reported in Table 1. The results of the unit root tests (without structural breaks), including the tests of Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), Breitung (2000), Levin et al. (2002) (LLC) and Im et al. (2003) (IPS), for CO_2 emissions, energy intensity and the quadratic terms of GDP per capita and urbanisation show that the variables contain unit roots at their levels, implying that the variables are not stationary. There is an exception for the variable representing CO_2 emissions in the Breitung test, indicating that this variable is significant at the 5% level. All the coefficients for the first differences of the variables are significant at the 1% level, implying that all the variables are stationary at their first difference (Table 1). The results of the panel unit root tests with structural breaks following Carrion-i-Silvestre et al. (2005) (Table 2) show that the statistics reject the null hypothesis of stationarity for the variables when using both the homogeneous and heterogeneous long-run versions of the test. [3]

Overall, the results of the panel unit root tests with and without structural breaks for all the variables confirm that the level values of all the series are non-stationary and that all the variables are stationary at the first difference; that is, all variables are integrated of order one. Consequently, panel cointegration tests can be employed to study the long-run equilibrium process.

The panel cointegration tests of Westerlund (2007) and Johansen Fisher proposed by Maddala and Wu (1999) are applied to the three models. The results of the Johansen Fisher panel cointegration test from both a trace test and a maximum

[2] The results of all these tests are not provided here to conserve space, but they can be obtained from the authors upon request.

[3] The country-by-country tests with multiple breaks, allowing for a maximum of five breaks, are also calculated using Monte Carlo simulations based on 20,000 replications. The results are not provided here to save space, but they can be obtained from the authors upon request.

eigen value test indicate the existence of cointegration at the 1% significance level for each of the models (Table 3). The results of the Westerlund (2007) cointegration test are reported in Table 4. It can be observed that group-t and panel-t reject the null hypothesis of no cointegration in the three models. Therefore, the overall evidence from the Johansen Fisher and Westerlund (2007) tests for cointegration shows that there is a long-run relationship between the dependent and independent variables. The next subsection addresses this issue.

Table 1: Panel unit root tests without structural breaks for the variables used in Models I, II and III

Method	LR	LN	LCO_2	LP	LA	LIND	LS	LU	LPD	LA^2	LU^2	LEI
ADF												
Level	66.246	59.896	62.571	4.271	70.889	52.890	47.070	62.787	44.106	70.905	62.764	67.418
	(0.213)	(0.406)	(0.317)	(1.000)	(0.119)	(0.665)	(0.847)	(0.310)	(0.911)	(0.119)	(0.311)	(0.186)
First	576.129	476.156	436.893	-4.739	164.514	288.792	221.686	80.649	136.584	164.650	88.125	220.532
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.026)**	(0.000)***	(0.000)***	(0.006)***	(0.000)***
PP												
Level	18.682	72.556	63.448	16.738	33.266	31.542	38.933	0.318	31.097	33.272	46.878	70.900
	(1.000)	(0.094)*	(0.290)	(1.000)	(0.996)	(0.998)	(0.074)*	(1.000)	(0.998)	(0.996)	(0.851)	(0.119)
First	953.254	502.794	531.591	-2.542	178.791	332.740	384.467	97.195	78.324	178.834	97.122	699.758
difference	(0.000)***	(0.000)***	(0.000)***	(0.005)***	(0.000)***	(0.000)***	(0.000)***	(0.001)***	(0.038)**	(0.000)***	(0.001)***	(0.000)***
Breitung												
Level	6.170	-1.093	-2.287	5.636	4.629	0.395	1.608	5.079	0.274	4.625	3.396	1.384
	(1.000)	(0.137)	(0.011)**	(1.000)	(1.000)	(0.653)	(0.946)	(1.000)	(0.608)	(1.000)	(0.999)	(0.916)
First	-10.406	-8.048	-9.882	-1.150	-2.740	-9.394	-8.232	-15.262	-1.586	-2.744	-15.143	-3.505
difference	(0.000)***	(0.000)***	(0.000)***	(0.024)**	(0.003)***	(0.000)***	(0.000)***	(0.000)***	(0.056)*	(0.003)***	(0.000)***	(0.000)***
LLC												
Level	2.525	-0.971	-0.010	1.005	-0.997	-0.323	-0.325	3.377	3.661	-0.998	-0.618	-0.248
	(0.994)	(0.165)	(0.495)	(0.842)	(0.159)	(0.373)	(0.372)	(0.999)	(0.999)	(0.115)	(0.268)	(0.401)
First	-22.953	-18.642	-19.183	5.502	-5.221	-15.189	-9.343	-3.774	-3.478	-5.230	-3.642	-4.893
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
IPS												
Level	3.187	1.288	0.160	4.355	-1.289	1.910	1.142	0.374	6.971	-1.289	0.529	-0.098
	(0.999)	(0.901)	(0.563)	(1.000)	(0.098)*	(0.971)	(0.873)	(0.646)	(1.000)	(0.986)	(0.701)	(0.460)
First	-26.069	-21.815	-20.152	4.735	-7.629	-14.701	-10.833	-18.540	-5.408	-7.635	-4.719	-10.764
difference	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***

Note: In the panel unit root test without structural breaks, the probabilities of the test statistics are presented in parentheses. ***, ** and * indicate that the test statistics are significant at the 1%, 5% and 10% levels, respectively. Individual trends and constants are included in the tests, and the Schwarz Information Criterion (SIC) is used to determine the optimal lag length.

Table 2: Panel unit root tests with structural breaks for the variables used in Models I, II and III

Variables	Bartlett Kernel	Quadratic Kernel	Bootstrap critical values		
			5%	2.5%	1%
LN					
Homogeneous	8.893**	8.897**	8.711	8.991	9.123
Heterogeneous	9.710**	9.783**	9.512	9.703	10.111
LR					
Homogeneous	7.734**	7.611**	6.821	7.010	7.812
Heterogeneous	6.913***	6.742***	5.431	5.912	6.729
LCO_2					
Homogeneous	7.928**	7.929**	7.062	7.866	8.278
Heterogeneous	8.211	8.271	6.728	7.381	8.021
LP					
Homogeneous	6.744***	6.514**	6.323	6.510	6.711
Heterogeneous	6.918*	7.131*	6.891	7.452	7.859
LA					
Homogeneous	11.428***	11.888***	9.781	9.979	10.163
Heterogeneous	9.639***	9.519***	7.508	8.631	8.357
LU					
Homogeneous	10.249***	10.021**	8.363	9.472	10.236
Heterogeneous	9.381***	9.415***	7.501	8.993	9.303
LPD					
Homogeneous	5.326	5.461	5.513	5.815	6.012
Heterogeneous	4.964*	5.433*	4.959	5.572	5.630
LIND					
Homogeneous	9.316***	9.322***	7.703	8.110	8.741
Heterogeneous	8.120***	8.121***	5.504	6.823	7.330
LS					
Homogeneous	13.391*	13.731**	12. 831	13.555	13.789
Heterogeneous	12.097	12.280	13.561	13.829	13.995
LA^2					
Homogeneous	15.351*	16.281***	15.348	15.692	16.093
Heterogeneous	16.211*	16.836*	16.203	16.897	17.356
LU^2					
Homogeneous	13.612**	14.549***	12.462	13.112	13.899
Heterogeneous	15.721*	16.723**	15.564	16.714	17.231
LEI					
Homogeneous	18.715***	19.291***	17.348	17.702	18.367
Heterogeneous	20.248***	20.711***	18.826	20.210	21.245

Note: The number of structural breaks is limited to 5. ***, ** and * indicate that the test statistics are significant at the 1%, 2.5%, and 5% levels, respectively. The long-run variance is estimated using both the Bartlett and the Quadratic spectral kernels with automatic spectral window bandwidth selection as described in Sul et al. (2005). Furthermore, all bootstrap critical values allow for cross-sectional dependence.

Table 3: Johansen Fisher Cointegration Test for Models I, II and III

Model	Fisher statistic (from the trace test)	Fisher statistic (from the max eigen value test)
Model I		
None	626.8 (0.000)***	373.6 (0.000)***
At most 1	333.3 (0.000)***	202.0 (0.000)***
At most 2	182.1 (0.000)***	105.7 (0.000)***
At most 3	124.7 (0.000)***	99.24 (0.000)***
At most 4	105.2 (0.000)***	105.2 (0.000)***
Model II		
None	1543.0 (0.000)***	587.2 (0.000)***
At most 1	1161.0 (0.000)***	351.4 (0.000)***
At most 2	800.0 (0.000)***	217.8 (0.000)***
At most 3	519.9 (0.000)***	138.7 (0.000)***
At most 4	296.7 (0.000)***	121.4 (0.000)***
At most 5	180.7 (0.000)***	106.7 (0.000)***
At most 6	106.1 (0.000)***	106.1 (0.000)***
Model III		
None	1297.0 (0.000)***	729.4 (0.000)***
At most 1	861.1 (0.000)***	422.9 (0.000)***
At most 2	507.6 (0.000)***	234.0 (0.000)***
At most 3	315.6 (0.000)***	166.4 (0.000)***
At most 4	190.1 (0.000)***	124.3 (0.000)***
At most 5	117.5 (0.000)***	96.27 (0.001)***
At most 6	102.9 (0.000)***	102.9 (0.000)***

Note: The Schwarz Information Criterion (SIC) is used to determine the optimal lag length. *** indicates that the test statistics are significant at the 1% level.

Table 4: Westerlund Cointegration Test for Models I, II and III

Statistic	Value	*P*-value
Model I		
Group-t	-2.939	0.003***
Group-a	-11.387	0.865
Panel-t	-14.610	0.003***
Panel-a	-8.396	0.741
Model II		
Group-t	-3.107	0.064*
Group-a	-1.562	1.000
Panel-t	-9.055	0.000***
Panel-a	-0.843	1.000
Model III		
Group-t	-3.122	0.054*
Group-a	-3.938	1.000
Panel-t	-12.005	0.059*
Panel-a	-4.719	1.000

Note: *** and * indicate that the test statistics are significant at the 1% and 10% levels, respectively. Following Westerlund (2007), the maximum lag length is selected according to $4(T/100)^{2/9}$. The null hypothesis of the test is "no cointegration".

4.2 Estimation of the Long-Run Elasticities of CO_2 Emissions

The results of the regression analysis of the three models, Models I, II, and III, using the AMG estimator are presented in Table 5. Because the variables total population (*P*) and GDP per capita (*A*) are used in all three models, first the direction and magnitude of these variables with respect to CO_2 emissions in Models I and II are compared.[4] The results show that the total population and GDP per capita have positive and significant effects on CO_2 emissions, implying that increases in both the total population and GDP per capita lead to increases in CO_2 emissions. Although each model gives different magnitudes for the coefficients for the total population and GDP per capita, the coefficient for the total population is greater than that for GDP per capita in all three models. This result demonstrates that in the long run, the total population size contributes more to increased CO_2 emissions than economic growth in developed countries. This finding is consistent with those of Fan et al. (2006), Poumanyvong and Kaneko (2010) and Liddle (2011), who obtain the same results for developed countries. Liddle (2011) observes that environmental impact is more sensitive to changes in population growth than to changes in economic growth. This

[4] It is worth noting that in Model III, the coefficients for affluence and urbanisation cannot be interpreted directly as elasticity coefficients due to the inclusion of their quadratic terms. Thus, in Model III, the focus with respect to affluence and urbanization is only on whether the EKC hypothesis holds.

greater sensitivity occurs because population growth through the acceleration of energy consumption speeds up pollutant emissions.

With respect to the renewable energy consumption in Model I (Table 5), it is found that this variable has a negative and significant effect on CO_2 emissions, indicating that a 1% increase in renewable energy consumption reduces CO_2 emissions by 0.004% in the long run. Although the value is very small, the sign is as expected. This finding contrasts with the positive relationship between renewable energy consumption and CO_2 emissions found by Menyah and Wolde-Rufael (2010) for the US and Apergis et al. (2010) for a group of 19 developed and developing countries. The result obtained in this study substantiates the argument that the increased usage of renewable energy reduces pollutant emissions in OECD countries in the long run.

Non-renewable energy consumption has a positive and statistically significant effect on CO_2 emissions. The coefficient for non-renewable energy consumption suggests that a 1% increase in this factor leads to an increase in CO_2 emissions of 1.038%. It is apparent from the estimated coefficients that have positive effects on CO_2 emissions in Model I that the impact of non-renewable energy consumption on CO_2 emissions is much stronger than the effects of population and affluence.

The coefficients of the variables considered in Model II indicate that industrialisation, the contribution of services to GDP and urbanisation all are positively associated with CO_2 emissions. However, the effect of the contribution of services to GDP on CO_2 emissions is not significant. The coefficient for industrialisation is statistically significant at the 5% level, indicating that a 1% increase in industrialisation lead to increase CO_2 emissions by 0.319 per cent. Similar results have been found by York et al. (2003b), Shi (2003), Lin et al. (2009) and Zhang and Lin (2012) for different countries. It appears that industrialisation, through the extraction and consumption of raw materials, the emission of industrial pollutants and increased energy demand, can intensify CO_2 emissions.

With respect to the relationship between urbanisation and CO_2 emissions, it is found that a 1% increase in urbanisation increases CO_2 emissions by 0.462% in Model II. This result is consistent with the results of Poumanyvong and Kaneko (2010) for high-income countries and of Zhang and Lin (2012) for China. Likewise, Liddle and Lung (2010) find a positive association between urbanisation and CO_2 emissions from transport in OECD countries. These authors state that this is a surprising result because it is expected that greater urbanisation leads to more public transport use and thus to lower emissions. The direct relationship between urbanisation and CO_2 emissions contrasts with the results of Fan et al. (2006), who find that urbanisation negatively affects CO_2 emissions for high-income countries. In different studies, it can be observed that the relationship between urbanisation and emissions is complex, even in countries with the same levels of income and development. However, developed and largely urbanised countries are in a better position to achieve low carbon intensity by adopting new energy technologies. Hence, it seems that the relationship between urbanisation and emissions can be better explained by the EKC hypothesis in developed countries. The last variable investigated in Model II is population density, which has a negative but statically insignificant effect on CO_2 emissions.

Table 5: CO_2 Emissions Coefficients for the AMG Estimator

	Model I	Model II	Model III
LP	0.543 (4.31)***	2.677 (2.49)**	1.037 (6.69)***
LA	0.119 (13.55)***	0.570 (3.53)***	0.466 (8.10)***
LR	-0.004 (-1.81)*		
LN	1.038 (16.59)***		
LIND		0.319 (2.17)**	
LS		0.434 (1.44)	
LU		0.462 (2.57)**	0.175 (1.80)*
LPD		-0.411 (-.012)	
LA^2			0.237 (10.01)***
LU^2			-0.078 (-1.87)*
LEI			0.683 (11.11)***

Note: Statistics are presented in parentheses. ***, ** and * indicate that the test statistics are significant at the 1%, 5% and 10% levels, respectively.

Turning to Model III (Table 5), the results provide evidence supporting the EKC hypothesis for the association between urbanisation and CO_2 emissions because the coefficient for urbanisation is positive and significant and the coefficient for the quadratic term of urbanisation is negative and significant. These results indicate that at a higher level of urbanisation, CO_2 emissions decrease. In other words, when a certain level of urbanisation is achieved, emissions tend to decline in OECD countries. This finding confirms the ecological modernisation theory, which argues that if the environment and the economy are properly managed through structural changes or modernisation, emissions can be curbed. Therefore, as urbanisation is a key indicator of modernisation (Ehrhardt-Martinez et al. 2002; York et al. 2003a, 2003b), it is expected that at higher levels of urbanisation, the environmental impact decreases. In addition, Ehrhardt-Martinez (1998) explains this phenomenon by stating that the urbanisation process in its initial stages depends more on resource extraction. However, advanced urbanisation is accompanied by largely complete urban infrastructure as well as increased use of less-polluting fuels. Although Ehrhardt-Martinez (1998) claims that this reasoning might be true only for the relationship between urbanisation and the phenomenon of deforestation, according to the results obtained in this study, it seems it is also true for CO_2 emissions.

This result can also be explained based on observations and experiences in developed countries. The economy in urban areas is primarily service based rather than manufacturing based. Moreover, using nuclear and hydro energy for generating electricity is becoming more common in such areas. In addition, today, in some developed countries, most industrial activities have relocated to regions far from cities or even to other countries. Furthermore, strong investment in infrastructure and policies to extend public transport systems have led to increases in the levels of public transport usage. All these activities help reduce CO_2 emissions in urbanised areas. The inverted U-shaped relationship between urbanisation and CO_2 emissions is also supported by the findings of Martínez-Zarzoso and Maruotti (2011) for developing countries. However, this result is in contrast with those of York et al. (2003b) and Zhu et al. (2012), who find little evidence supporting the EKC hypothesis in the urbanisation–CO_2 emissions nexus.

The estimated long-run coefficients for GDP per capita and its square do not satisfy the EKC hypothesis because the coefficients for both GDP per capita and its quadratic term are positive and significant. Unlike the previous result for the urbanisation–CO_2 emissions nexus, the result for the affluence–CO_2 emissions nexus contradicts the expectation of the modernisation perspective. It may be concluded that environmental impacts follow an EKC in association with urbanisation rather than economic development per se (Ehrhardt-Martínez 1998; Ehrhardt-Martinez et al. 2002 and York et al. 2003b). Finding no evidence in support of the EKC hypothesis is in line with the results of Martínez-Zarzoso and Bengochea-Morancho (2004), Richmond and Kaufman (2006) and Iwata et al. (2010) for OECD countries. This finding also supports those of York et al. (2003a) and Martínez-Zarzoso and Maruotti (2011), who investigate the EKC with respect to income and emissions using the STIRPAT model. However, the latter finding is contrary to those results indicating that there is an inverted U-shaped association between income and emissions, including the results of Dijkgraaf and Vollebergh (2001) and Liu (2005) for OECD countries.

The last variable included in Model III is energy intensity, which has a positive and significant effect on CO_2 emissions at the 1% level. The related coefficient demonstrates that an increase in energy intensity increases CO_2 emissions by 0.683% in the long run. This finding is as expected and is supported by the results of Cole and Neumayer (2004) for 86 countries and of Poumanyvong and Kaneko (2010) for low- to high- income countries.

4.3 Granger Causality

This section provides the results of the causality test for the variables used in Model I and Model II.[5] The results of the panel error correction model for Model I and Model II are reported in Table 6 and Table 7, respectively. The findings are interpreted only for the relationships between CO_2 emissions and the other variables. Beginning with Model I and the short-run effects (Table 6), total population, GDP per capita and non-renewable energy consumption have positive and significant effects on CO_2 emissions, implying these three variables do Granger-cause CO_2 emissions in the short run.

The coefficient for renewable energy consumption is negative; however, it is not statistically significant. This result indicates that renewable energy use does not Granger-cause CO_2 emissions in the short run. The results also show that CO_2 emissions have a positive effect on the total population and a negative effect on GDP per capita in the short run. However, both the coefficients are statistically insignificant. Interesting results are found with respect to the effect of CO_2 emissions on renewable and non-renewable energy consumption. The impact of CO_2 emissions on renewable energy use is positive and statistically significant; suggesting that increases in CO_2 emissions can stimulate the use of renewable sources. The

[5] All variables used in Model III except for energy intensity are included in Model II.

coefficient for CO_2 emissions with respect to non-renewable energy use is negative and statistically significant, implying that increases in CO_2 emissions may contribute to reductions in the use of non-renewable sources, even in the short term.

Table 6: Panel Causality Test for Model I

Dependent Variables	Source of causation (independent variable)					
	Short run					Long run
	ΔLCO_2	ΔLP	ΔLA	ΔLR	ΔLN	ECT
ΔLCO_2	–	0.145 (1.93)*	0.093 (1.66)*	-0.006 (-0.34)	0.945 (66.57)***	-0.684 (-14.93)***
ΔLP	0.002 (0.53)	–	0.005 (0.13)	-0.002 (-0.94)	-0.003 (-1.76)*	-0.002 (-0.44)
ΔLA	-0.095 (-1.63)	0.884 (2.96)***	–	0.008 (1.24)	0.099 (1.63)	0.037 (0.47)
ΔLR	1.079 (2.20)**	-6.902 (-0.54)	-0.450 (-1.49)	–	-0.339 (-0.68)	-0.550 (-0.82)
ΔLN	-0.737 (-29.74)***	0.063 (1.81)	0.033 (1.92)*	-0.006 (-0.23)	–	-0.610 (-13.29)***

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistics are significant at the 1%, 5% and 10% levels, respectively. The optimal lag length for the variables is two and is determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

The empirical results presented in Table 6 indicate that there is unidirectional causality from the total population size to CO_2 emissions. Similarly, a unidirectional causality from GDP per capita to CO_2 emissions is obtained in the short run for OECD countries. This result is consistent with the findings of Salim and Rafiq (2012) for the Philippines. However, this finding contrasts with the unidirectional causality from CO_2 to income found by Salim and Rafiq (2012) for India. This result is also contrary to the findings of Apergis et al. (2010), Menyah and Rufael (2010a) and Salim and Rafiq (2012), who find bidirectional causality between income and emissions for a mix of developed and developing countries. Finding unidirectional causality from CO_2 emissions to renewable energy consumption is in line with the results of Menyah and Wolde-Rufael (2010) for the US. However, this result is contrary to the bidirectional causality between emissions and renewable energy consumption found by Salim and Rafiq (2012) for Brazil, China and India. In addition, this finding is also in contrast to the results of Payne (2012), who finds no causal relationship between renewable energy use and CO_2 emissions in the US. Finally, as shown in Table 6, there is bidirectional causality between non-renewable energy consumption and CO_2 emissions. This finding is not directly comparable to the results of previous studies because most of those studies use total energy consumption.

Turning to the long-run causality relationship in Model I (Table 6), the coefficients for the lagged error correction terms (ECT) are negative and significant at the 1% level for the equations in which CO_2 emissions and non-renewable energy use are dependent variables. This finding indicates that bidirectional causality exists between CO_2 emissions and non-renewable energy consumption in the long run. Furthermore, the coefficients for the error correction terms also suggest that the deviations in CO_2 emissions and non-renewable energy consumption from the short run to the long run are corrected by 68% and 61%, respectively, each year and that convergence towards equilibrium after a shock to CO_2 emissions or non-renewable energy consumption takes 1.4 and 1.6 years, respectively.

Moving to the short-run effects in Model II (Table 7), the causal relationships between total population and CO_2 emissions and between GDP per capita and CO_2 emissions remain the same as those in Model I; that is, they are unidirectional from total population and GDP per capita to CO_2 emissions. The coefficients for the other variables indicate that the effects of industrialisation, urbanisation and population density on CO_2 emissions are negative, whereas the effect of the contribution of services to GDP is positive. However, only the coefficients for the contribution of services to GDP and population density are statistically significant. This result implies that although industrialisation and urbanisation do not Granger-cause CO_2 emissions, the contribution of services to GDP and population density do Granger-cause CO_2 emissions in the short run. The effect of CO_2 emissions as the independent variable on the other variables as the dependent variables from Table 7 shows that CO_2 emissions have a negative and significant effect on the contribution of services to GDP in the short run, suggesting there is bidirectional causality between CO_2 emissions and the contribution of services to GDP and unidirectional causality running from population density to CO_2 emissions. A positive effect of the contribution of services to GDP on emissions in the short run indicates that in OECD countries, due to increases in services industries, more energy is required for lighting, heating and cooling, electronics use and transportation.

Although the relationship between population density and CO_2 emissions in the long run is not significant, finding a negative and significant association between these variables in the short run indicates that the population density contributes to emissions mitigation. However, it seems that there are other stronger factors that can make this association insignificant in the long run.

The results of the long-run causality presented by the ECT in Model II (Table 7) reveal that in the equations in which CO_2 emissions and industrialisation are dependent variables, the ECTs are -0.811 and -0.227, respectively. These values demonstrate that total population, GDP per capita, industrialisation, the contribution of services to GDP, urbanisation and population density Granger-cause CO_2 emissions in the long run. Moreover, these results indicate that CO_2 emissions, total population, GDP per capita, the contribution of services to GDP, urbanisation and population density Granger-cause industrialisation in the long run. Furthermore, the results indicate that the variables adjust towards a long-run equilibrium level within 1.2 and 4.4 years after a shock occurs.

Table 7: Panel Causality Test for Model II

Dependent Variables	Source of causation (independent variable)							
	Short run							Long run
	ΔLCO_2	ΔLP	ΔLA	$\Delta LIND$	ΔLS	ΔLU	ΔLPD	ECT
ΔLCO_2	–	0.412 (1.72)*	0.553 (11.46)***	-0.074 (-1.42)	0.258 (2.98)***	-0.101 (-0.19)	-0.869 (-1.67)*	-0.811 (-12.92)***
ΔLP	0.001 (0.68)	–	-0.002 (-0.91)	-0.001 (-0.34)	-0.005 (-1.50)	-0.030 (-1.16)	-0.235 (-9.99)***	-0.002 (-1.05)
ΔLA	-0.250 (-1.56)	0.998 (2.50)**	–	0.162 (4.77)***	0.512 (9.32)***	-0.604 (-1.06)	-0.275 (-0.77)	-0.227 (-5.92)***
$\Delta LIND$	-0.013 (-0.55)	0.877 (2.11)**	0.139 (3.83)***	–	1.153 (25.99)***	-0.215 (-1.66)*	-0.514 (-2.36)**	0.002 (0.06)
ΔLS	-0.029 (-2.13)**	-0.316 (-1.36)	0.162 (8.07)***	0.400 (27.00)***	–	0.327 (1.65)	0.016 (1.88)*	0.011 (0.49)
ΔLU	0.003 (0.62)	-0.008 (-0.34)	-0.005 (-0.62)	0.003 (1.80)*	0.006 (1.78)*	–	-0.009 (-0.43)	-0.003 (-1.55)
ΔLPD	0.001 (0.62)	-0.297 (-8.17)***	0.001 (0.63)	-0.006 (-2.12)**	-0.008 (-1.66)*	0.002 (0.07)	–	-0.002 (-0.67)

Note: *z*-statistics are presented in parentheses. ***, ** and * indicate that the test statistics are significant at the 1%, 5% and 10% levels, respectively. The optimal lag length for the variables is two and is determined by the Akaike and the Schwarz Information Criteria. ECT indicates the estimated error correction term.

5. Conclusion

This article attempts to explore the determinants of CO_2 emissions using three different models based on a statistical method, STIRPAT, for OECD countries over the period from 1980 to 2011. First, it simultaneously compares the effects of renewable and non-renewable energy consumption on CO_2 emissions in the short- and long run. Second, the effects of industrialisation, the contribution of the service sector to GDP and population density on CO_2 emissions are investigated. Finally, the relationship between urbanisation and CO_2 emissions is examined in the context of the EKC hypothesis.

The empirical results show that renewable energy consumption has a negative and significant effect on CO_2 emissions, whereas non-renewable energy consumption has a positive and statistically significant effect on CO_2 emissions in the long-run. The results also reveal that the total population size, GDP per capita, industrialisation and urbanisation have positive and significant effects on CO_2 emissions. Finally, the findings provide evidence supporting the EKC hypothesis for the relationship between urbanisation and CO_2 emissions in OECD countries in the long run. The Granger causality results indicate that there is unidirectional causality from CO_2 emissions to renewable energy consumption, from total population to CO_2 emissions, from GDP per capita to CO_2 emissions and from population density to CO_2 emissions. Moreover, bidirectional causality is found between non-renewable energy consumption and CO_2 emissions and between the contribution of services to GDP and CO_2 emissions.

The empirical evidence indicates that renewable energy consumption plays an important role in reducing CO_2 emissions. Therefore, to achieve steady and sustainable growth in renewable energy use, governments should design and implement effective support policies to promote investment in new renewable energy technologies. In addition, increasing the population density seems to be another key strategy for reducing pollutant emissions that should be considered by policy makers. Generally, congestion and spatial density reduce personal vehicle use and promote less motorised travel. Finally, urban planners should take serious action on climate change through improving public transportation systems, improving the energy efficiency of buildings and increasing the share of renewable energy sources in energy supplies.

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