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Examining the Linkages among Carbon Dioxide Emissions, Electricity Production and Economic Growth in Different Income Levels

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Abstract: Our industrialized world highly depends on fossil fuels to cover its energy needs. Although fossil fuels have been linked with economic growth, their use has also been found to have severe impacts on the environment. The linkages among carbon dioxide emissions, energy consumption and economic growth have been extensively examined in the current literature. The present study focuses on electricity production from fossil fuels, as well as from renewable sources and examines their linkages with CO_2 emissions and economic growth in 119 world countries of different income levels, by assessing Granger causality. In addition, the Environmental Kuznets Curve (EKC) hypothesis is tested, in order to evaluate whether economic growth and carbon dioxide emissions are linked with an inverse U-shaped relationship and with an N-shape relationship in higher income levels. The EKC hypothesis is confirmed for high income and upper-middle income countries, but not for lower-middle and low income levels and a bidirectional Granger causality is found between GDP per capita and CO_2 per capita in all income levels.

Keywords: CO_2 emissions; electricity production; Environmental Kuznets Curve; fossil fuels; renewables; economic growth; income levels

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1. Introduction

The rapid economic growth that followed the industrial revolution had a major impact on the environment. Fossil fuels were the core of the new industrialized world and their use started growing rapidly, reaching millions of tons of oil equivalents by today [1]. This excessive use and burning led to the emission of greenhouse gases (GHG) into the atmosphere which, in large amounts, contribute to global warming and climate change [2].

Carbon dioxide (CO_2) emissions are the number one anthropogenic contributor to climate change, since they constitute 81% of total GHG emissions for 2018. At the same time, CO_2 emissions that come from fossil fuel and industrial processes constitute 65% of total GHG emissions (according to 2010 data) [3]. These emissions are expected to increase even more: global population is expected to rise to approximately 9 billion by 2050 [4] and, therefore, world energy consumption is expected to rise nearly 50% between 2018–2050 [5].

In 1992, the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol in 1997, made it obvious that, in order to avoid a disastrous effect on the environment, it is essential to reduce the world's GHG emissions to a large extent [2]. Even so, according to recent data, there seems to be a 61.62% increase of total CO_2 emissions (kt) in the world from 1990 until 2016 [6]. At the same time, fossil fuel energy consumption, as a percentage of total energy use, has not changed significantly and energy use (kg of oil equivalent per capita) has increased by 15.6% in the period 1990–2014 [7]. All these data emphasize the urgent need to implement CO_2 emissions reduction measures, by limiting the use of fossil fuels and switching to renewable energy sources instead [8].

Energy consumption seems to be the main cause of the large CO_2 emissions. At the same time, higher energy consumption leads to higher economic development [9].

According to Adams et al. [10], if non-renewable energy consumption increases by 10%, economic growth will increase by 2.11%, but if renewable energy consumption increases by 10%, economic growth will increase by 0.27%. This is why many scientists argue that a reduction in CO_2 would have a negative outcome for economic growth, something that would be an undesired result in developed and, especially, in developing countries [9]. The links and the relationship between energy consumption, CO_2 emissions and economic development have been intensively studied in the last decades [11].

The linkages among CO_2 emissions and electricity production have not been widely examined in the current literature. This study aims to contribute to the existing literature and examines the causality among economic growth, electricity production and CO_2 emissions in 119 world countries, categorized by income status (high, upper-middle, and lower-middle and low income), over the period of 2000–2018. Countries of different income levels are expected to have substantial differences regarding the relationships that exist among these factors and their identification is significantly important, since it can provide a better understanding and important knowledge for policy makers, in order to implement targeted measures for an efficient energy transition and the achievement of global sustainability. This study examines and assesses all these different linkages, for a large number of world countries classified by income with recent data, something that has not been widely investigated in the current literature. To achieve that, panel data are collected and the linkages between CO_2 emissions, electricity production from fossil fuels, electricity production from renewable sources and GDP per capita are investigated, while taking into consideration population density as well. Static and dynamic regression models are constructed, an in-depth econometric analysis is conducted, the Environmental Kuznets Curve is assessed for each income level and Granger causality is tested.

The paper is organized as follows: Section 2 presents recent economic and energy data, as well as data regarding CO_2 emissions that come from different energy sources. Section 3 includes an in-depth literature review on the examined field and Section 4 presents used data and methodology. In Section 5, the results are presented and in Section 6 the results are discussed. Section 7 concludes the paper.

2. Recent World Data

The world's GDP has increased rapidly over the last twenty years, from $33.624 trillion in 2000 to $87.799 trillion in 2019 (Figure 1), according to the World Bank database [12]. Over the same time period, global population increased from 6.114 billion in 2000 to 7.674 billion in 2019 [13], meaning that GDP per capita increased from $5499.151 in 2000 to $11,441.733 in 2019 [14].

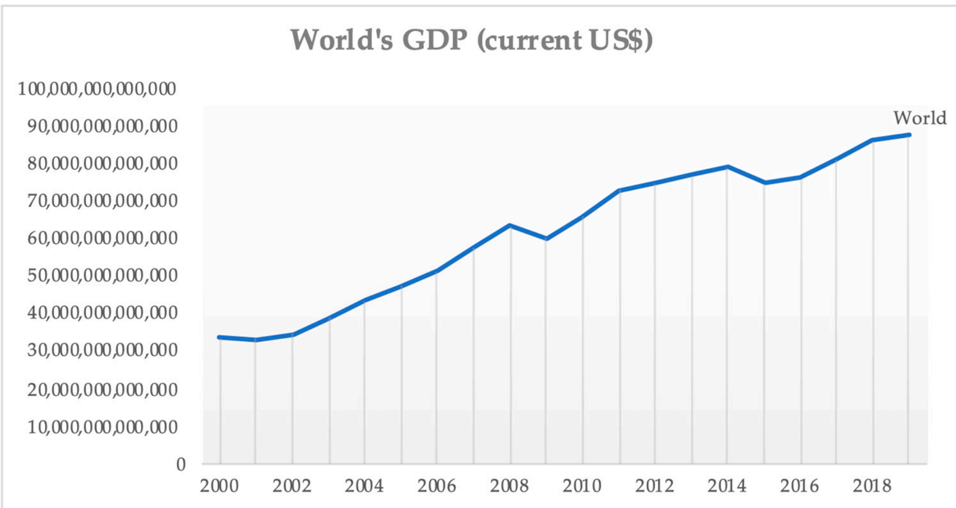


Figure 1. World's GDP (current US$) (Data source: World Bank [12]).

Focusing on the energy sector, world's total final energy consumption reached 9,937,702 kilotonnes of oil equivalent in 2018 [15]. The industrial sector and the transportation sector were the highest consumers of world's total energy supply (Figure 2) and fossil fuels were energy's main provider. According to IEA data [16], in 2017, the share of renewables in world's final energy consumption was estimated at 17.3%. The residential sector was the highest consumer of renewable energy supply (Figure 3).

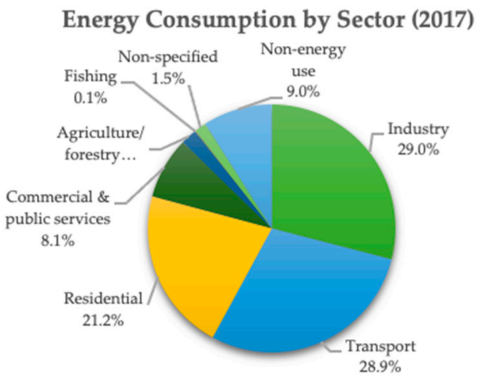


Figure 2. Energy Consumption by Sector in 2017 (Data source: IEA [15]).

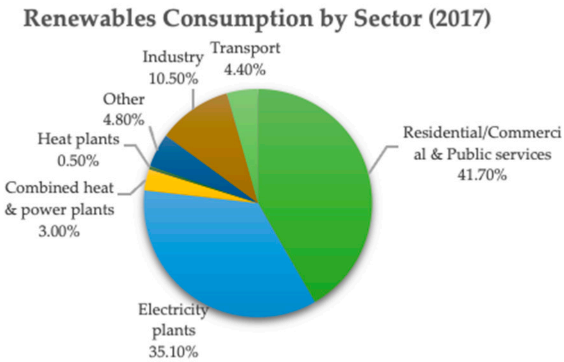


Figure 3. Renewables Consumption by Sector in 2017 (Data source: IEA [16]).

World's total CO_2 emissions reached 33,513.3 Mt of CO_2 in 2018 [17], estimating thus the per capita emissions at 4.4 tonnes CO_2 [18]). Coal was the energy source that was responsible for most of energy-related CO_2 emissions in the world, while oil followed [19] (Figure 4). In addition, world's total forest area has decreased over the last two decades; from 40,556,022.3 km^2 in 2000, it decreased to 39,958,245.9 km^2 in 2016, according to the World Bank database [20].

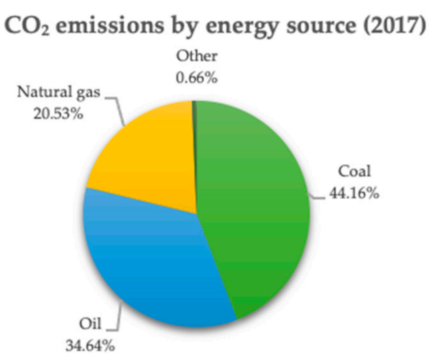


Figure 4. CO_2 emissions by energy source in 2017 (Data source: IEA [17]).

3. Literature Review

The existing literature about links and relationships between energy consumption, environmental pollution and economic growth is divided into three categories. The first category concerns the investigation of the CO_2 Environmental Kuznets Curve hypothesis. According to the EKC hypothesis, environmental pressure in an economy starts growing as the income grows, reaches a peak and, after a certain level of income, starts reducing [21]. This happens because, as a nation tries to develop, uses its natural resources with no concerning on the environmental degradation; after a certain income level, and since environmental degradation can lead to various problems, nations focus on improving environmental quality and protecting the environment [22]. Based on the EKC hypothesis, an inverted U-shaped relationship exists between economic development and environmental degradation. For high income countries, the EKC hypothesis has a cubic and not a quadratic form and an N-type curve is observed, indicating that even higher levels of GDP per capita lead to an increase of environmental degradation [23]. The EKC has significant implications for sustainability [24].

A plethora of studies have been carried out in which this hypothesis is tested, starting from 1991 and the empirical study by Grossman and Krueger [9]. A variety of recent studies have examined and evidenced the CO_2 EKC hypothesis for various different regions [25–30]; in contrast, some recent studies that have found that the EKC hypothesis wasn't valid for certain regions also exist in the literature [31–34].

The second category concerns the research of causality among economic growth and energy consumption. These studies examine the hypothesis that growth in economy is related to growth in energy use and they test that relationship using time series models, usually with Granger causality and cointegration models. Mehrara [35], Narayan and Smyth [36], Apergis and Payne [37], Ozturk et al. [38] and Apergis and Payne [39], among others, have examined this hypothesis.

The third category combines the previous two categories by examining the relationship among economic growth, energy consumption (renewable and non-renewable), CO_2 emissions and other variables (urbanization, trade, etc.). These studies examine the argument that economic growth has a long-term influence on energy consumption and pollution growth [9]. Wang et al. [40] have found a bidirectional causality between CO_2 emissions and energy consumption and between economic growth and energy consumption among 28 provinces in China, while energy consumption and economic growth are found to be the cause for CO_2 emissions in the long run. Lu [41] has also reached the same results in his study for 24 Asian countries. Lin and Moubarak [42], in their study for China, have found a bidirectional causality between renewable energy consumption and economic growth, although they found no causality between carbon emissions and renewable energy consumption. Pao and Tsai [43] have evidenced a bidirectional causality between income, energy consumption and emissions in Brazil, while Pao et al. [44] have found the same results for Russia. In contrast, Lotfalipour et al. [9] in their study on Iran, found a unidirectional causality from economic growth to CO_2 emissions and no causality from fossil fuels consumption to CO_2 emissions. Also, Soytas et al. [45] in their study for the United States, found no Granger causality between income and CO_2 emissions and between energy use and income.

Some recent studies have been focusing specifically on European countries and the relationship between economic growth, energy consumption and carbon emissions that exists. Examples of those studies include the following: Acaravci and Ozturk [46] examined these relationships for 19 European countries and found a long run relationship between CO_2 emissions, energy consumption and economic growth only for specific countries. They also confirmed the EKC hypothesis in Denmark and Italy. Pirlogea and Cicea [47] also examined the links between energy consumption and economic growth and found that there is a unidirectional causality from renewable energy consumption to economic growth in Romania and from energy consumption (natural gas) to economic growth in Spain on short-run, concluding that there is a long run equilibrium between economic growth and energy consumption in every EU country. Bölük and Mert [11] have tested the EKC hypothesis in 16 EU countries and they concluded that the EKC hypothesis was not valid in these countries. Kasman and Duman [48] examined the causality among energy consumption, economic growth, CO_2 emissions, taking also into consideration the trade openness and urbanization, for 15 European countries. They provided evidence that support the EKC hypothesis and they found a unidirectional causality from energy consumption, trade openness and urbanization to CO_2 emissions, among others. Alper and Oguz [49] examined the relationship between economic growth, renewable energy consumption, capital and labor for six EU countries and concluded that renewable energy consumption has a positive impact on economic growth for all 6 countries.

The examination of the Energy-Environmental Kuznets Curve (EEKC) has also been a topic of interest in the literature and has been assessed on a global and regional scale. More specifically, various studies have been focusing on the examination of the linkages that exist between economic growth and energy consumption. Some studies have managed to confirm the existence of the EEKC globally and regionally [50–52], while a plethora of studies exist that could not confirm the hypothesis [53–55].

Regarding the linkages that exist among CO_2 emissions, electricity production and economic growth, fewer studies have been focusing on that. For instance, in a recent study for Ghana, it was found that a bidirectional causality exists from hydroelectric sources' electricity production to CO_2 emissions, while a unidirectional causality is found from CO_2 emissions to renewables and waste energy production, as well as from CO_2 emissions to fossil fuels electricity production (oil, gas and coal), among others [56]. For the case of Pakistan, it was found that, among others, a weak unidirectional causality exists from CO_2 emissions to electricity production, both from natural gas and oil [57]. Focusing on Europe, and more specifically on the case of Italy, the EKC hypothesis has been validated, while it has been found that in fact electricity production per capita that comes from renewable sources can lead to a reduction of CO_2 emissions per capita, both short-term and long-term [58].

Only a few studies in the literature have studied these linkages and have tested the EKC hypothesis for different income levels. For example, Al-Mulali et al. [59] investigated the EKC hypothesis for different income groups, while taking into consideration the Ecological Footprint instead of CO_2 emissions to stand for environmental degradation. The authors confirmed the EKC hypothesis only for high income and upper-middle income countries, while the hypothesis was not valid for lower-middle and low incomes. Similarly, Ulucak and Bilgili [60] followed a similar approach, using the Ecological Footprint and classifying the studied countries by income. The authors confirmed the EKC hypothesis for all income levels. In addition, Aruga [52] examined the EEKC hypothesis for 19 Asia-Pacific countries, depending on income, and the results indicated that the EEKC hypothesis was confirmed only for high income countries, and not for low and middle income.

As it is highlighted, there is a plethora of studies that examine the causality among economic growth, energy consumption and carbon dioxide emissions, using different econometric procedures and techniques and their results differ substantially. This study aims to provide a comprehensive approach with recent data, focusing specifically on electricity production and including 119 world countries categorized by income level, assessing thus the different relationships that exist among these factors in different income groups. The study contributes to the existing literature, by combining all the above elements with an in-depth econometric analysis that is followed.

4. Materials and Methods

4.1. Data

Panel data were collected from the International Energy Agency (IEA) and the World Bank Database for 119 world countries and for the period 2000–2018. These countries were categorized based on their income level, as it has been identified by the World Bank, that takes into consideration GNI per capita (current USD) to divide the countries to four different income groups. The newest classifications were set on July 2020 and the thresholds are presented in Table 1 [61]. The 119 countries for which data were collected and that were included in the analysis are presented in Figure 5, classified by income level: 47 countries are identified as high income countries, 33 as upper-middle income countries, 32 as lower-middle income countries and 7 as low income countries. The indicators for which data were extracted are presented in Table 2.

Table 1. Income classification thresholds, as set by the World Bank.

Income Level	Threshold (July 2020)
High income	>12,535
Upper-middle income	4046–12,535
Lower-middle income	1036–4045
Low income	<1036

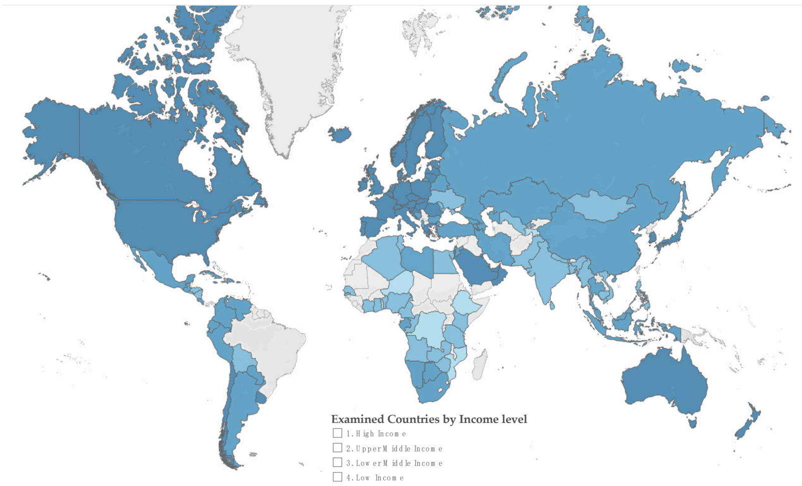


Figure 5. The 119 countries included in the analysis, by income level.

Table 2. Extracted indicators and data sources.

	Source	Indicator	Measurement
1	IEA [62]	Total electricity production	GWh
2	WB [13]	Population	total
3	WB [63]	Electricity production from oil, gas and coal sources	% of total
4	WB [64]	Electricity production from renewable sources, excluding hydroelectric	% of total
5	WB [65]	Electricity production from hydroelectric sources	% of total
6	WB [66]	CO_2 emissions	Metric tons per capita
7	WB [14]	GDP per capita	Current US$
8	WB [67]	Population density	People per sq. km of land area

Indicators 4&5 were combined, in order to create a variable that refers to electricity production from renewable sources, including hydroelectric. Indicators 1&2 were used to estimate electricity production per capita, so that electricity production from fossil fuels (*EPFpc*) and renewable sources (including hydroelectric) per capita (*EPRpc*) will be estimated, based on the indicators 3&4. Forecasts were provided, relying on exponential smoothing, in order to complete the missing data for the last few years wherever it was necessary. To achieve that, various forecast accuracy measures were examined, such as Mean Absolute Percentage Error—MAPE, Mean Square Deviation—MSD, etc.

4.2. Econometric Methodology

The EKC curve and the relationship and causality between CO_2 emissions and GDP, electricity production from fossil fuels per capita, electricity production from renewable sources per capita and population density were examined, based on the following methodology.

Before performing the regression analysis, several econometric tests are conducted to address different problems that might occur. A usual problem when working with panel data is variables' correlation; in order to determine if the time-series are cross-sectional independent, Pesaran's cross-section dependence test is used. OLS Dummy estimator (FEM) allowing for individual fixed effects with Driscoll-Kraay standard errors can assist in the correction of the variance-covariance matrix, in cases where the time series are found to be cross-sectional dependent. For Random Effects, Breusch-Pagan LM test for individual effects is applied and robust standard errors are required.

In cases where cross-section dependence is evidenced, unit root tests are performed. Dickey-Fuller and Augmented Dickey-Fuller tests can be performed when analyzing panel data, with the issue of homogeneity in the autoregressive parameter. Fisher type tests do not adopt this restrictive assumption and they don't require strongly balanced panels. The asymptotic behavior of the time series (T) and the cross-section dimensions (N) should be taken into consideration when performing unit root tests. Fisher type tests can be used in cases where T and N tend to infinity, but the number of panels with no unit root must raise at the same rate as N.

In cases of non-stationarity, panel cointegration tests are performed: more specifically, Westerlund test are performed to check for panel cointegration, based on the significance of the error correction term in the error correction model. Westerlund proposed four cointegration tests: the G_t and G_a statistics, which test the null hypothesis of no cointegration for all cross-sectional units, rejecting the hypothesis in cases of cointegration for at least one unit, and the P_t and the P_a statistics, which reject the hypothesis in cases of cointegration of the panel in total. In addition, the causal relationships among the studied factors are examined by conducting Granger causality tests. Granger causality can help identify whether the relationship between two variables is unidirectional, bidirectional or if no causality exists between them [68,69].

Three different data sets are constructed: one for high income countries (47 countries), one for upper-middle income countries (33 countries) and one for lower-middle & low income countries (39 countries). After the data collection, their combination and the extraction of the necessary variables, Box-Cox tests have been used, in order to test linear against logarithmic forms. Quadratic regression models, as well as a cubic regression model were constructed, in order to examine the linkages among the studied variables, considering CO_2 emissions per capita as a dependent variable and GDP per capita, per capita electricity production from fossil fuels, per capita electricity production from renewables and population density as independent variables. The general forms of these models are:

$$Y_{it} = a + X_{it}\beta_{it} + X_{it}^2\beta_{it} + \delta_i + \gamma_i + \varepsilon_{it} \tag{1}$$

$$Y_{it} = a + X_{it}\beta_{it} + X_{it}^2\beta_{it} + X_{it}^3\beta_{it} + \delta_i + \gamma_i + \varepsilon_{it} \tag{2}$$

where Y_{it} is the dependent variable, X_{it} an independent variables' k-vector, δ_i and γ_i the cross-section and period specific effects, that can be either fixed or random, and ε_{it} the disturbance terms. After modification, the proposed models that include only the statistically significant variables, become:

$$CO2pc_{it} = a + \beta_{1it}GDPpc_{it} + \beta_{2it}GDPpc_{it}^2 + \beta_{3it}EPFpc_{it} + \beta_{4it}EPRpc_{it} + \beta_{5it}Dens_{it} + \delta_i + \gamma_i + \varepsilon_{it} \tag{3}$$

$$CO2pc_{it} = a + \beta_{1it}GDPpc_{it} + \beta_{2it}GDPpc_{it}^2 + \beta_{3it}GDPpc_{it}^3 + \beta_{4it}EPFpc_{it} + \beta_{5it}EPRpc_{it} + \beta_{6it}Dens_{it} + \delta_i + \gamma_i + \varepsilon_{it} \tag{4}$$

In Equations (3) and (4), *CO2pc* stands for CO_2 emissions per capita, *GDPpc* for GDP per capita, *EPFpc* for electricity production from fossil fuels (oil, gas and coal) per capita, *EPRpc* for electricity production from renewable sources per capita (including hydroelectric) and *Dens* for population density.

To estimate the panel data models, the ordinary least squares (OLS) method was chosen and Fixed and Random Effects methods were applied; the choice of the appropriate method depends on the way that a_i is handled (fixed predefined number or random expulsion from a particular distribution). In the case of Random Effects, Hausman tests are also conducted, in order to check for inconsistencies in the RE estimations. The literature also suggests the use of fully modified ordinary least squares (FMOLS), a reliable non-parametric method that assists in tackling problems related to variables' endogeneity and serial correlation [70,71]. FMOLS estimators seem to perform significantly well in cases where the time series dimension is bigger than the cross sectional dimension [70]. In the present study, and since the cross sectional dimension is significantly bigger than the time series dimension, Fixed Effects with Driscoll-Kraay standard errors were chosen to be used, when modeling the static analysis. This way, the problem of cross-section dependence is prioritized and addressed.

In addition to the OLS method, and in order to capture the dynamic nature of the model, Generalized Method of Moments (GMM) was used for estimation, in terms of Orthogonal Deviations. GMM is used in statistical models in order to provide estimators for the parameters that are consistent, as well as asymptotically normally distributed [72]. It is a significantly important method for econometrics and is widely used in economics, since it can be applied in various models (linear/non-linear, cross-section, time series and panel data, etc.) [73]. In cases where moment conditions can be obtained, while the likelihood function cannot, GMM combines the moments and provides efficient estimators [74]. GMM assists in avoiding endogeneity, since it extends the static model, by including lagged variables that help control the problem, as well as in avoiding the problems of autocorrelation and reverse causation [75,76]. Due to the many advantages that come with its use, Generalized Method of Moments was chosen over dynamic ordinary least squares (DOLS), a parametric method that uses lagged terms and assists in endogeneity and serial correlation problems [77,78].

GMM minimizes the following Equation (5), regarding β:

$$M\ (\beta) = \left(\sum_{i=1}^{N} \Psi_i'\, u_i(\beta)\right) W \left(\sum_{i=1}^{N} \Psi_i'\, u_i(\beta)\right) = \zeta(\beta)' W \zeta(\beta) \tag{5}$$

In this equation, W is a pxp weighting matrix, Ψi is a $T_i xp$ instruments matrix for cross section i and $u_i(\beta) = (\Upsilon_i - f(X_{it}, \beta))$. White robust covariances are used to calculate the weighting of matrix W and the coefficient covariance estimates are:

$$\left(\frac{M^*}{M^* - k^*}\right)\left(\sum_t X_t' X_t\right)^{-1}\left(\sum_t X_t' \hat{u}_t \hat{u}_t{}' X_t\right)\left(\sum_t X_t' X_t\right)^{-1} \tag{6}$$

In Equation (6), M^* is the total number of stacked observations and k^* equals to the number of estimated parameters. According to Arellano and Bond [79], in orthogonal deviations each observation is seen as a deviation from the average of future observations and each deviation is weighted, in order to standardize the variance:

$$x_{it}^* = \left[x_{it} - \left(x_{i(t+1)} + \ldots + x_{iT}\right)/(T-t)\right]\sqrt{(T-t)}/\sqrt{T-t+1} \tag{7}$$

The (T_i-q) equations for individual unit (i) are:

$$Y_i = \delta w_i + d_i \eta_i + \nu_i \tag{8}$$

5. Results

5.1. Descriptive Statistical Analysis

The indicators presented in Table 2 were analyzed and combined, so that the necessary variables could be extracted, such as per capita electricity production from fossil fuels and from renewable sources. Table 3 presents the descriptive statistics of the indicators that were used in the analysis for high income countries.

Table 3. Descriptive Statistics of High income countries.

	EPFpc	EPRpc	CO2pc	GDPpc	Dens
Mean	0.004684	0.003144	10.39119	32,195.14	336.1680
Median	0.003691	0.000939	8.072146	27,729.19	109.5809
Maximum	0.021955	0.056814	67.31050	118,823.6	7952.998
Minimum	0.00000331	0	0.251345	1659.908	2.493134
Std. Dev.	0.004552	0.007736	8.274268	21,106.53	1028.928
Skewness	1.748568	4.755374	2.960003	1.164747	5.988748
Kurtosis	5.968018	28.28739	15.53083	4.738511	39.83826
Jarque-Bera	782.8296	27158.6	7146.537	314.3716	55,831.77
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

The highest levels of electricity production from fossil fuels, throughout the studied time-period and among the 47 high income countries that were examined, were observed in Bahrain (0.021955 GWh/capita in 2006), while the lowest levels were observed in Uruguay (0.00000331 GWh/capita in 2003). Respectively, the highest levels regarding electricity production from renewable sources were observed in Iceland (0.0568 GWh/capita in 2015), while zero levels were observed in various countries throughout the studied time-period.

Qatar was the country with the highest levels of CO_2 emissions per capita for the whole time-period, with the highest being observed in 2001 (67.31 metric tons per capita); some of the lowest levels of CO_2 emissions per capita were observed in Malta and Uruguay. At the same time, in Luxembourg were observed the highest levels of GDP per capita, reaching $118,823.65 in 2014, while the lowest GDP per capita levels were observed in Romania ($1659.9 in 2000). The highest population density was observed in Singapore for the whole time-period (7952.998 people/sq.km in 2018), while the lowest population density was observed in Australia (2.49 people/sq.km in 2000).

Similarly, Table 4 presents the descriptive statistics for upper-middle income countries and Table 5 for lower-middle and low income countries. The highest levels of electricity production from fossil fuels, among the 33 upper-middle income countries were observed in Libya (0.005999 GWh/capita in 2013), while zero levels were observed in Paraguay and Albania for various years. Similarly, the highest levels of electricity production from renewable sources were observed in Paraguay (0.010049 GWh/capita in 2000), while zero levels were observed in Libya for the whole time period and in Botswana for the years 2000–2012.

Table 4. Descriptive Statistics of Upper-middle income countries.

	EPFpc	EPRpc	CO2pc	GDPpc	Dens
Mean	0.001757	0.000913	4.215383	5545.145	72.05436
Median	0.001421	0.000494	3.306489	4986.676	65.22279
Maximum	0.005999	0.010049	15.6463	19288.6	270.9931
Minimum	0	0	0.657959	622.7421	2.179756
Std. Dev.	0.001496	0.001577	3.090284	3226.249	58.80999
Skewness	0.751483	4.073107	1.262113	1.008053	1.092193
Kurtosis	2.593474	20.94012	4.227859	4.117945	4.357204
Jarque-Bera	63.3315	10141.95	205.8481	138.8408	172.7788
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5. Descriptive Statistics of Lower-middle and Low income countries.

	EPFpc	EPRpc	CO2pc	GDPpc	Dens
Mean	0.000432	0.000232	1.139077	1470.063	134.9511
Median	0.000188	0.000133	0.611946	1133.186	73.57522
Maximum	0.002133	0.002499	15.1386	5591.212	1239.579
Minimum	0	0	0.01628	111.9272	1.543177
Std. Dev.	0.000575	0.000372	1.584955	1133.959	192.4295
Skewness	1.481985	4.07663	3.406818	1.232556	3.601976
Kurtosis	3.86273	22.02623	19.41762	3.9178	18.42611
Jarque-Bera	294.221	13229.1	9755.384	213.6282	8949.486
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000

The highest levels of CO_2 emissions were observed in Kazakhstan for the whole time period (15.65 metric tons per capita in 2011) and high levels were observed in the Russian Federation as well; the lowest levels of carbon dioxide emissions were observed in Paraguay for most of the studied years (0.658 metric tons per capita in 2005). Among the studied upper-middle income countries, Venezuela had the highest GDP per capita and Armenia had the lowest. Population density was higher in Jamaica for the whole studied time period (270.99 people/sq.km in 2018) and lower in Namibia for the whole time period (2.18 people/sq.km in 2000).

In the case of lower-middle & low income countries, the highest levels of electricity production from fossil fuels were observed in Ukraine (0.00213 GWh/capita in 2012), while zero levels were observed in Nepal, Ghana and the Republic of the Congo in various years. The highest levels of electricity production from renewable sources were observed in Tajikistan (0.0025 GWh/capita in 2005), while zero levels were observed in Niger, Mongolia and Benin for various years.

Mongolia presented the highest levels of CO_2 emissions for various years (15.14 metric tons per capita in 2013), while the Democratic Republic of the Congo presented the lowest levels for the whole time period (0.016 metric tons per capita in 2001). The highest GDP per capita was observed in Algeria ($5591.2 in 2012), while the lowest levels of GDP per capita were observed in Ethiopia ($111.93 in 2002). The highest levels of population density were observed in Bangladesh throughout the whole time period (1239.56 people/sq.km in 2018), while the lowest levels of population density were observed in Mongolia through the whole time period (1.54 people/sq.km in 2000).

By comparing the means, it can be observed that the highest levels of per capita electricity production from fossil fuels, as well as from renewable sources, were found in high income countries, while lower-middle & low income countries had significantly lower levels. The same can be concluded regarding CO_2 per capita levels: there are obvious differences in the levels of high income, upper-middle income and lower-middle & low income countries, with high income countries being those who pollute more. Population density was, on average, higher in high income countries and lower in upper-middle income countries.

5.2. Cross-Section Dependence and Unit Roots

Pesaran CD test is performed for each different data set, in order to test for cross-section dependence. The results reject the null hypothesis in all cases and suggest the existence of cross-section dependence (Table 6), indicating that unit root tests should be conducted. In addition, these results suggest the use of Driscoll-Kraay standard errors in the static regression models, in order to correct the variance-covariance matrix.

Table 6. Cross-section dependence (Pesaran CD test).

Variables	High Income	Upper-Middle Income	Lower-Middle & Low Income
EPFpc	23.065 *** [0.0000]	36.613 *** [0.0000]	31.038 *** [0.0000]
EPRpc	5.98 *** [0.0000]	6.94 *** [0.0000]	6.639 *** [0.0000]
CO2pc	40.812 *** [0.0000]	22.051 *** [0.0000]	54.969 *** [0.0000]
GDPpc	118.973 *** [0.0000]	85.592 *** [0.0000]	102.98 *** [0.0000]
Dens	46.212 *** [0.0000]	35.446 *** [0.0000]	94.99 *** [0.0000]

Note: The null hypothesis assumes that there exists no cross-section dependence (correlation). Significance at *** 1%.

Unit root tests are performed for each data set separately (Tables 7–9). The performed unit root tests (Fisher-ADF and Fisher PP) indicate that the examined variables are I(1) and evidence of stationarity exist in first differences.

Table 7. Fisher-ADF & Fisher-PP panel unit root test for high income countries.

Variables	Fisher—ADF	Fisher—PP		Fisher—ADF	Fisher—PP
Levels			*First Differences*		
EPFpc	55.3359 [0.9995]	66.67 [0.9853]	EPFpc	335.237 *** [0.0000]	871.135 *** [0.0000]
EPRpc	40.692 [1.0000]	705398 [0.8861]	EPRpc	308.303 *** [0.0000]	1128.62 *** [0.0000]
CO2pc	51.7633 [0.9999]	66.174 [0.9869]	CO2pc	336.321 *** [0.0000]	1207.49 *** [0.0000]
GDPpc	74.3357 [0.9331]	40.9579 [1.0000]	GDPpc	289.557 *** [0.0000]	389.16 *** [0.0000]
Dens	103.584 [0.2343]	79.5754 [0.8559]	Dens	232.967 *** [0.0000]	181.673 *** [0.0000]

Note: The null hypothesis assumes that the variable contains unit root. *P*-values in brackets. Significance at *** 1%.

Table 8. Fisher-ADF & Fisher-PP panel unit root test for upper-middle income countries.

Variables	Fisher—ADF	Fisher—PP		Fisher—ADF	Fisher—PP
Levels			*First Differences*		
EPFpc	46.8653 [0.9642]	66.8678 [0.4470]	EPFpc	257.191 *** [0.0000]	738.596 *** [0.0000]
EPRpc	23.9952 [1.0000]	28.9385 [1.0000]	EPRpc	273.322 *** [0.0000]	1072.02 *** [0.0000]
CO2pc	25.4143 [1.0000]	23.1849 [1.0000]	CO2pc	231.818 *** [0.0000]	743.485 *** [0.0000]
GDPpc	38.4883 [0.9973]	27.3549 [1.0000]	GDPpc	175.707 *** [0.0000]	273.061 *** [0.0000]
Dens	78.4815 [0.1397]	70.7227 [0.3230]	Dens	474.520 *** [0.0000]	229.837 *** [0.0000]

Note: The null hypothesis assumes that the variable contains unit root. *P*-values in brackets. Significance at *** 1%.

Table 9. Fisher-ADF & Fisher-PP panel unit root test for lower-middle & low income countries.

Variables	Fisher—ADF	Fisher—PP		Fisher—ADF	Fisher—PP
Levels			*First Differences*		
EPFpc	54.6241 [0.9796]	50.7312 [0.9929]	EPFpc	225.482 *** [0.0000]	674.029 *** [0.0000]
EPRpc	74.4705 [0.5923]	71.3106 [0.6907]	EPRpc	290.486 *** [0.0000]	1154.4 *** [0.0000]
CO2pc	47.9935 [0.9970]	54.6955 [0.9792]	CO2pc	275.946 *** [0.0000]	1002.39 *** [0.0000]
GDPpc	35.1546 [1.0000]	32.7017 [1.0000]	GDPpc	195.040 *** [0.0000]	546.373 *** [0.0000]
Dens	66.5735 [0.6584]	28.7294 [1.0000]	Dens	324.933 *** [0.0000]	124.692 *** [0.0006]

Note: The null hypothesis assumes that the variable contains unit root. *P*-values in brackets. Significance at *** 1%.

5.3. Cointegration

In order to test for panel cointegration, Westerlund panel cointegration tests are performed for each data set separately. The null hypothesis of no cointegration is rejected from the G_t and G_a statistics in almost every case, implying cointegration for at least one unit, as well as from the P_t and P_a statistics in almost every case, implying cointegration for the whole panel (Tables 10–12).

Table 10. Westerlund Panel Cointegration Test for high income countries.

Equation	Gt	Ga	Pt	Pa
CO2pc = f(GDPpc)	−5.665 *** [0.000]	−21.79 *** [0.000]	−30.947 *** [0.000]	−21.182 *** [0.000]
CO2pc = f($GDPpc^2$)	−5.681 *** [0.000]	−24.376 *** [0.000]	−32 *** [0.000]	−21.387 *** [0.000]
CO2pc = f($GDPpc^3$)	−5.742 *** [0.000]	−25.911 *** [0.000]	−33.582 *** [0.000]	−22.771 *** [0.000]
CO2pc = f(EPFpc)	−5.913 *** [0.000]	−21.832 *** [0.000]	−32.825 *** [0.000]	−17.976 *** [0.000]
CO2pc = f(EPRpc)	−5.335 *** [0.000]	−21.844 *** [0.000]	−35.717 *** [0.000]	−25.058 *** [0.000]
CO2pc = f(Dens)	−6.118 *** [0.000]	−12.374 [0.312]	−31.202 *** [0.000]	−9.953 [0.126]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

Table 11. Westerlund Panel Cointegration Test for upper-middle income countries.

Equation	Gt	Ga	Pt	Pa
CO2pc = f(GDPpc)	−4.974 *** [0.000]	−18.636 *** [0.000]	−25.683 *** [0.000]	−17.946 *** [0.000]
CO2pc = f(GDPpc^2)	−5.047 *** [0.000]	−19.918 *** [0.000]	−24.775 *** [0.000]	−20.762 *** [0.000]
CO2pc = f(GDPpc^3)	−5.080 *** [0.000]	−21.058 *** [0.000]	−25.619 *** [0.000]	−21.604 *** [0.000]
CO2pc = f(EPFpc)	−5.165 *** [0.000]	−18.395 *** [0.000]	−26.173 *** [0.000]	−17.93 *** [0.000]
CO2pc = f(EPRpc)	−5.232 *** [0.000]	−19.344 *** [0.000]	−24.499 *** [0.000]	−22.053 *** [0.000]
CO2pc = f(Dens)	−6.119 *** [0.000]	−3.307 [0.998]	−20.493 *** [0.000]	−3.956 [0.999]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

Table 12. Westerlund Panel Cointegration Test for lower-middle & low income countries.

Equation	Gt	Ga	Pt	Pa
CO2pc = f(GDPpc)	−4.896 *** [0.000]	−14.962 *** [0.002]	−28.97 *** [0.000]	−17.059 *** [0.000]
CO2pc = f(GDPpc^2)	−5.119 *** [0.000]	−15.827 *** [0.000]	−28.624 *** [0.000]	−18.073 *** [0.000]
CO2pc = f(GDPpc^3)	−5.129 *** [0.000]	−17.464 *** [0.000]	−28.318 *** [0.000]	−18.782 *** [0.000]
CO2pc = f(EPFpc)	−5.117 *** [0.000]	−17.313 *** [0.000]	−27.646 *** [0.000]	−17.906 *** [0.000]
CO2pc = f(EPRpc)	−4.493 *** [0.000]	−18.4 *** [0.000]	−26.339 *** [0.000]	−19.398 *** [0.000]
CO2pc = f(Dens)	−6.021 *** [0.000]	−2.731 [0.999]	−12.693 [0.710]	−3.51 [0.998]

Note: The null hypothesis assumes no cointegration. Significance at *** 1%.

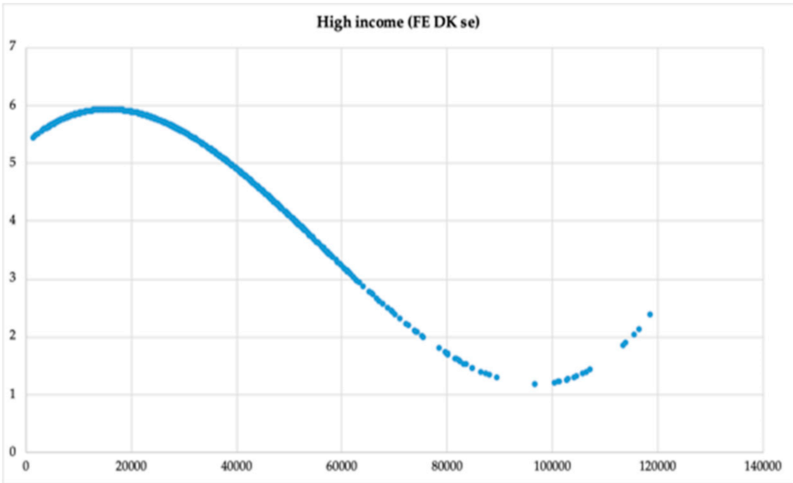
5.4. Regression Results

Six different regression models are constructed, in order to examine the existence of EKC curve and the relationships among the studied variables in different income levels. The Hausman tests imply the use of fixed effects model specifications and columns 2, 4 and 6 present the results of FE Driscoll-Kraay standard errors, as it was indicated by the Pesaran CD tests (Section 5.2).

The regression results for high income countries indicate that GDP per capita is a driver of CO_2 emissions per capita, by both Fixed Effects Method and GMM. An N-shaped curve is found to connect the studied variables in the static model, confirming the hypothesis that even higher income levels can increase environmental degradation. In the dynamic model, an inverted U-shape relationship is found to connect GDP per capita and CO_2 emissions per capita, supporting the existance of an inverted U-shaped curve and confirming the EKC hypothesis. The results for upper-middle income countries also confirm the EKC hypothesis, since an inverted U-shape curve is found to connect GDP per capita and CO_2 emissions per capita, in both static and dynamic models. In contrast, the EKC hypothesis is not confirmed in lower-middle & low income countries. The static model implies a positive monotonic relationship between GDP per capita and carbon dioxide emissions, while the dynamic model supports the existance of a U-shape relationship between the two variables. Figure 6 presents graphically these relationships between GDP per capita and CO_2 emissions for all three different income levels, in both static and dynamic models.

Electricity production from fossil fuels is found to be a significant driver of CO_2 emissions, in every model, both static and dynamic, and for each one of the three income levels. Electricity production from renewable sources is found to be linked with an inverse relationship with CO_2 emissions, in the dynamic model of high income countries and in both static and dynamic models of lower-middle and low income countries, while it is statistically insignificant in the models of upper-middle income countries. Population density is found to be linked with an inverse relationship with CO_2 emissions, in both static and dynamic model of upper-middle income countries, while it is a small driver in the dynamic models of high income and lower-middle and low income countries.

The lag of the dependent variables is an autoregressive-distributed lag specification that ends up to an AD (1,0) formulation, where insignificant variables dynamics aren't included. All variables are assumed to be strictly exogenous, except the lagged dependent. Lagged variables in the dynamic models have a value less than 1 and are statistically significant (1% level), indicating a strong conditional convergence.



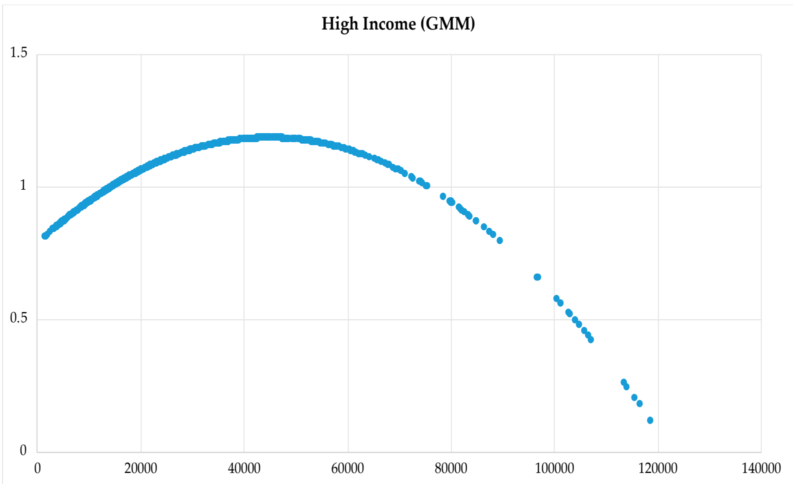
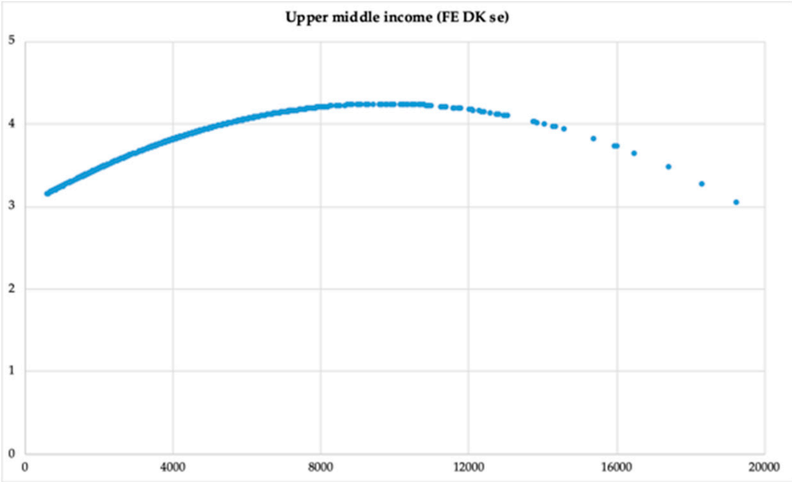
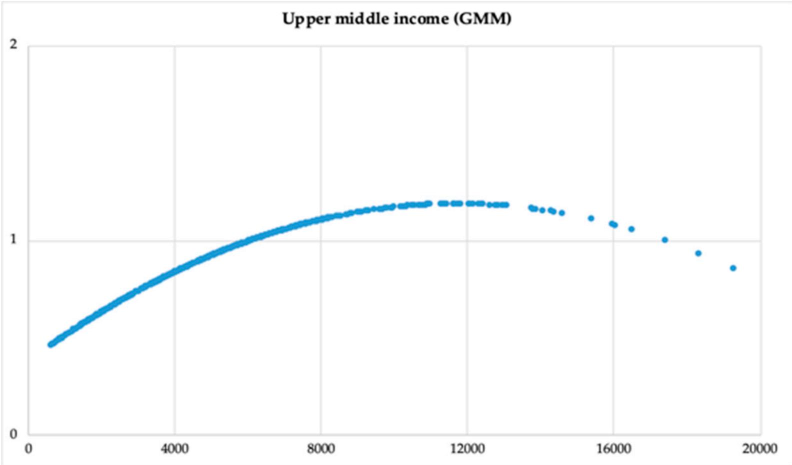


Figure 6. *Cont.*





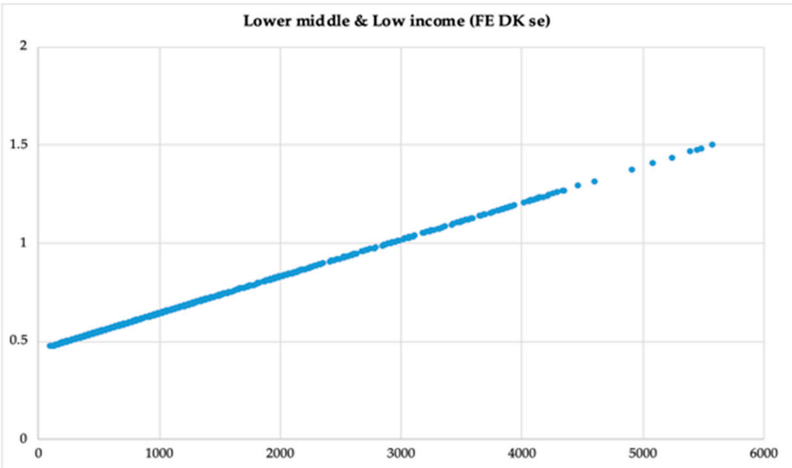


Figure 6. *Cont.*

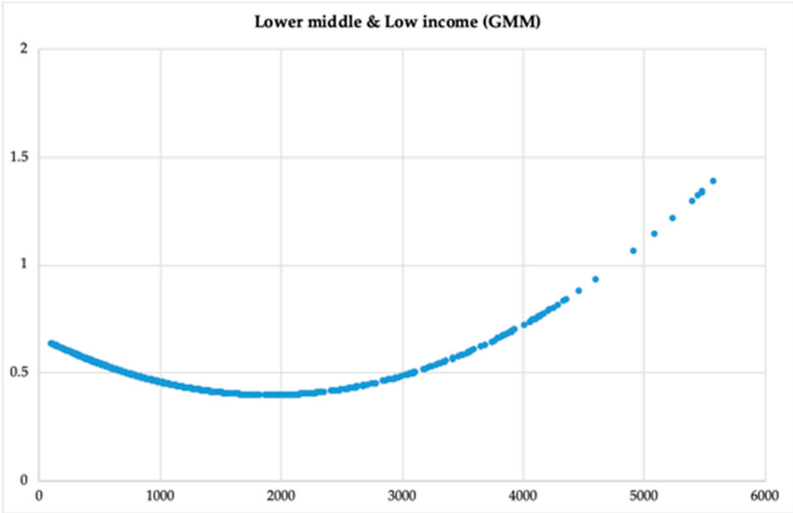


Figure 6. Derived relationships, where x axis represents GDP per capita and y axis CO_2 emissions per capita.

Since a lagged coefficient that equals 0 is an indication of instant adjustment, while a lagged coefficient that equals 1 is an indication of no adjustment [80], it is observed that the dynamic models of high income and lower-middle & low income countries present a slower adjustment to the equilibrium values, compared to the dynamic model of upper-middle income countries. More specifically, in the model of high income countries, the adjustment coefficient equals to 1–0.78. Since the lag coefficients show the adjustment to the equilibrium values, it can be seen that this adjustment equals to 22%, meaning that 22% of the discrepancy between actual and desired levels of efficiency is eliminated in a year; therefore, more than four periods are required for this adjustment. Similarly, the results of the lower-middle & low income countries model indicate that the adjustment coefficient equals to 1–0.67, meaning that 33% of the discrepancy between actual and desired levels is eliminated in a year and that approximately three periods will be required for this adjustment. In contrast, the dynamic model for upper-middle income countries presents an adjustment coefficient equal to 1–0.37, meaning that 63% of the discrepancy is eliminated in a year and that less than two periods will be required for the adjustment.

Both Wald tests of joint significance and Sargan tests of over-identifying restrictions are asymptotically distributed as χ^2 variables. Parentheses in Table 13 present the degrees of freedom. It can be seen that Sargan statistic does not reject the hypothesis of over-identifying restrictions and there is evidence of serially uncorrelated errors. AR(1) and AR(2) are first and second order serial autocorrelation tests, which indicate that the hypotheses of absence of autocorrelation is not rejected.

5.5. Granger Causality

In order to identify the relationships and the causality between the studied factors, Granger causality was examined for each one of the three datasets. Stacked test (with common coefficients) was chosen and 2 lags were included.

The results indicate that a bidirectional causality exists between GDP per capita and CO_2 emissions in all three different income levels, confirming the linkages that exist between these factors. A bidirectional causality is also found between GDP per capita and per capita electricity production from fossil fuels for high income and lower-middle & low income countries, while in the case of upper-middle income countries, a unidirectional causality is confirmed from electricity production from fossil fuels to GDP per capita.

Table 13. Regression results with CO2pc as dependent variable.

	High Income		Upper-Middle Income		Lower-Middle and Low Income	
	FE (DK se)	**GMM**	**FE (DK se)**	**GMM**	**FE (DK se)**	**GMM**
CO2(-1)		0.778178 *** (806.523)[0.0000]		0.373367 *** (28.541) [0.0000]		0.66676 *** (366.9915) [0.0000]
GDPpc	0.0000818 *** (4.17) [0.0001]	1.78E−05 *** (19.66458) [0.0000]	0.0002558 *** (12.39) [0.0000]	0.000138 *** (40.96653) [0.0000]	0.0001871 *** (2.91) [0.009]	−0.000283 *** (−72.10892) [0.0000]
GDPpc^2	−0.000000003 *** (−4.85) [0.000]	−0.000000000197 *** (−19.83668) [0.0000]	−0.0000000131 *** (−7.2) [0.0000]	−0.00000000587 *** (−18.86284) [0.0000]		0.0000000737 *** (77.43749) [0.0000]
GDPpc^3	0.0000000000000177 *** (3.99) [0.001]					
EPFpc	1144.766 *** (9.48) [0.000]	1277.639 *** (280.942) [0.0000]	947.1906 *** (10.09) [0.0000]	463.3203 *** (25.78434) [0.0000]	1664.963 *** (11.37) [0.000]	381.1654 *** (49.16397) [0.0000]
EPRpc		−451.2071 *** (−41.62376) [0.0000]			−669.3433 *** (−3.08) [0.006]	−153.8469 *** (−6.690689) [0.0000]
Dens		0.00427 *** (133.5502) [0.0000]	−0.0181993 *** (−8.08) [0.0000]	−0.018673 *** (−12.3941) [0.0000]		0.0000698 *** (3.230135) [0.0013]
within R^2	0.3105		0.5794		0.2478	
Hausman	13.56 *** [0.0011]		90.33 *** [0.0000]		4.79 * [0.0912]	
Wald test		598234.3 (5)		8420.45 (4)		35743.48 (5)
Sargan test		47.65923 (42)		28.71 (28)		31.4265 (33)
AR(1)		−2.285 ** [0.0223]		−2.362 ** [0.0182]		−2.288 ** [0.0221]
AR(2)		−0.7995 [0.4240]		−1.025 [0.3054]		−0.9359 [0.3493]
Shape of curve	N–shape	InvertedU–shape	Inverted U–shape	Inverted U–shape	Line	U–shape
Turning points	15859.25 56497.18	45177.67	9763.36	11754.69		1919.95
Observations	893	799	627	561	741	663

Note: t-Statistics in parentheses and *p*-values in square brackets. Parentheses in Wald and Sargan tests indicate degrees of freedom. Critical values for the Wald test of overall significance of the explanatory variables: $\chi^2_{0.05,5} = 11.07$, $\chi^2_{0.05,4} = 9.488$. Critical values for the Sargan test for over-identifying restrictions: $\chi^2_{0.05,42} = 58.124$, $\chi^2_{0.05,28} = 41.337$, $\chi^2_{0.05,33} = 47.4$. Significance at *** 1%, ** 5% and * 10%.

A unidirectional causality is also found from electricity production from fossil fuels to CO_2 emissions per capita, only for high income and lower-middle & low income countries, while this relationship is not confirmed in the case of upper-middle income countries. Instead, a causal relationship is found from CO_2 emissions to electricity production from fossil fuels for upper-middle income countries. In the case of high income countries, a bidirectional causality is found between GDP per capita and per capita electricity production from renewable sources, as well as between CO_2 emissions and population density. Electricity production from fossil fuels is found to Granger cause population density, in high income and lower-middle & low income countries. In lower-middle & low income countries, unidirectional causal relationships are also found from per capita electricity production from renewable sources to electricity production from fossil fuels and from population density to electricity production from renewables and to GDP per capita as well (Table 14).

Table 14. Granger Causality Results.

Null Hypothesis	High Income	Upper-Middle Income	Lower-Middle and Low Income
EPRpc does not Granger Cause *EPFpc*	0.1435 [0.8663]	0.84386 [0.4306]	8.49424 *** [0.0002]
EPFpc does not Granger Cause *EPRpc*	0.22982 [0.7947]	1.66069 [0.1909]	2.2018 [0.1114]
CO2pc does not Granger Cause *EPFpc*	1.14026 [0.3203]	5.78463 *** [0.0033]	1.68477 [0.1863]
EPFpc does not Granger Cause *CO2pc*	6.58308 *** [0.0015]	0.2931 [0.7461]	10.4235 *** [0.00003]
GDPpc does not Granger Cause *EPFpc*	9.3199 *** [0.0001]	0.78258 [0.4577]	4.17817 ** [0.0157]
EPFpc does not Granger Cause *GDPpc*	11.7925 *** [0.000009]	5.672 *** [0.0036]	5.40786 *** [0.0047]
Dens does not Granger Cause *EPFpc*	1.90495 [0.1495]	1.58869 [0.2051]	1.27445 [0.2803]
EPFpc does not Granger Cause *Dens*	7.17602 *** [0.0008]	0.51733 [0.5964]	4.85094 *** [0.0081]
CO2pc does not Granger Cause *EPRpc*	0.112 [0.8941]	0.90316 [0.4059]	0.5376 [0.5844]
EPRpc does not Granger Cause *CO2pc*	0.17197 [0.8420]	0.39549 [0.6735]	1.11302 [0.3292]
GDPpc does not Granger Cause *EPRpc*	4.5241 ** [0.0111]	0.85324 [0.4266]	0.29639 [0.7436]
EPRpc does not Granger Cause *GDPpc*	11.4263 *** [0.00001]	0.65071 [0.5221]	0.60933 [0.5440]
Dens does not Granger Cause *EPRpc*	0.00811 [0.9919]	2.22833 [0.1087]	2.52252 * [0.0810]
EPRpc does not Granger Cause *Dens*	0.0213 [0.9789]	0.43188 [0.6495]	0.0277 [0.9727]
GDPpc does not Granger Cause *CO2pc*	5.4029 *** [0.0047]	10.2292 *** [0.00004]	4.74665 *** [0.0090]
CO2pc does not Granger Cause *GDPpc*	3.1871 ** [0.0418]	19.8117 *** [0.000000005]	4.78144 *** [0.0087]
Dens does not Granger Cause *CO2pc*	13.151 *** [0.000002]	0.81525 [0.4431]	0.55917 [0.5720]
CO2pc does not Granger Cause *Dens*	3.64024 ** [0.0267]	0.26402 [0.7681]	1.38006 [0.2523]
Dens does not Granger Cause *GDPpc*	0.60785 [0.5448]	1.34882 [0.2604]	5.72788 *** [0.0034]
GDPpc does not Granger Cause *Dens*	1.38 [0.2522]	1.70387 [0.1829]	0.2997 [0.7411]
Observations	799	561	663

Note: t-Statistics in parentheses and p-values in square brackets. Rejection at *** 1%, ** 5% and * 10%.

6. Discussion

The present study confirms the existence of an inversed U-shaped curve for the 47 high income countries in the dynamic model and for the 33 upper-middle income countries in both static and dynamic quadratic model. These results suggest that environmental degradation increases along economic growth, but after a certain income level starts reducing. This indicates that, after reaching a certain level of growth, environmental measures and policies are promoted and there is a higher flow of resources towards environmental protection. At the same time, the results confirm the existence of an N-shaped curve in the static model of high income countries, confirming the assumption that, in high income countries, environmental degradation grows at first, as income grows, then starts reducing, after a certain income level, but it is once again increased at higher levels of GDP per capita [23]. Thus, it can be assumed that, in higher income levels, the existent measures and policies that had initially assisted in improving environmental conditions are not sufficient anymore, leading once more to an increase in environmental degradation. In the case of lower-middle and low income countries, the EKC hypothesis is not confirmed. The static model indicates a monotonic relationship where CO_2 emissions per capita increase as GDP per capita increases, while the dynamic model suggests the existence of a U-shape curve, meaning that in low income levels, GDP per capita has a negative effect on carbon dioxide emissions and it is only after a specific threshold ($1919.95 per capita) that higher GDP per capita increases CO_2 emissions and leads to environmental degradation. Thus, it can be seen that lower-middle & low income countries have to focus on other issues and on their growth and do not have the resources to invest in environmental protection.

The estimated turning points in the case of the static high income countries model, compared to the maximum GDP per capita observed in the studied period for the 47 high income countries, indicate that at least one country existed in the years 2000–2018 that had passed the second turning point and as GDP per capita increased, environmental degradation increased, too. The estimated turning point of the dynamic model for the high income countries indicates, compared to the same maximum GDP per capita, that there were countries that had passed this turning point as well and that they were in significantly higher GDP per capita levels. In the case of upper-middle income countries, the estimated turning points of both models indicate that there were countries that had passed the turning points and while their GDP per capita increased, their carbon dioxide emissions decreased. The estimated turning point of the dynamic lower-middle & low income countries model indicates that there were countries in the period 2000–2018 that had passed this turning point and their carbon dioxide emissions increased, as their GDP per capita increased.

Electricity production from fossil fuels is found to be a significant driver of CO_2 emissions in each one of the studied income levels, both in static and in dynamic models, confirming once again the negative environmental results that come with the use of fossil fuels. In addition, an inverse relationship exists between electricity production from renewable sources and carbon dioxide emissions, confirming thus the fact that higher percentages of electricity production covered from renewables can have a positive impact on the environment, reducing CO_2 emissions and, therefore, combating climate change.

Population density is linked with an inverse relationship with carbon dioxide emissions in the upper-middle income countries model, meaning that an increase in population density would lead to a decrease in CO_2 emissions. These results are also confirmed by various studies in the literature [81,82]. In contrast, the dynamic models of high income countries and lower-middle and low income countries suggest that population density is a small driver of CO_2 emissions.

This study also highlights the existence of a bidirectional Granger causality between GDP per capita and CO_2 emissions, while GDP per capita Granger causes per capita electricity production from fossil fuels in all income levels. This confirms the fact that the use of fossil fuels for electricity can indeed lead to economic growth while, at the same time, higher economic growth leads to a more intense use of fossil fuels in high income countries and lower-middle and low income levels. In addition, a unidirectional causality exists from per capita electricity production from fossil fuels to CO_2 emissions per capita in high income levels and lower-middle and low income levels, meaning that the use of fossil fuels leads to environmental degradation, while an increase in economic growth leads to an increase in air pollution. Per capita electricity production from renewable sources is found to Granger cause GDP per capita and, therefore, boost economic growth, only in high income countries, while in upper-middle and lower-middle & low income levels, this causality is not confirmed. This means that, in the period 2000–2018, the use of fossil fuels for electricity production in upper-middle and lower-middle and low income countries was necessary, in order to boost their economic growth.

The adjustment coefficients that were estimated in the GMM models indicate that 22% of the discrepancy between actual and desired levels is eliminated in a year in high income countries, 33% in lower-middle and low income countries and 63% in upper-middle income countries. It is obvious that the adjustment coefficients of the quadratic and the cubic model differ significantly. These results indicate that in low income levels, the adjustment of efficiency is relatively slow while, as income grows, the adjustment becomes faster. In higher income levels, the adjustment becomes slower again.

7. Conclusions and Policy Implications

The linkages between energy consumption, carbon dioxide emissions and economic growth have been extensively studied in the literature, as well as the causality existing among them. Especially in the case of environmental degradation and economic development, a variety of studies have been focusing on the Environmental Kuznets Curve hypothesis, which assumes that these two factors are linked with an inverse U-shaped relationship, while an N-shaped relationship is assumed to exist for high income countries.

This study aims to contribute to the existing literature, by examining the causal relationships that exist among carbon dioxide emissions, economic growth and electricity production from fossil fuels, as well as from renewable sources, for 119 world countries, classified based on their income levels, and for the years 2000–2018, while taking into consideration population density as well.

The results confirm the EKC hypothesis and the existence of an inverted U-shape curve in the dynamic model for high income countries and in both static and dynamic models for upper-middle income countries. The static model for high income countries confirms the N-shape curve, that is also confirmed in the literature, while the EKC hypothesis is not confirmed for lower-middle and low income countries. These results indicate that, lower-middle & low income countries do not have the resources required to invest in measures and policies related to environmental protection, since they have to focus on other issues regarding their development and growth. In contrast, upper-middle income countries, after reaching a certain level of growth, can promote measures and invest in environmental protection. The same is assumed for high income countries, according to the dynamic model; the static model for high income countries suggests that after a higher level of income, environmental degradation starts to increase again, indicating that all strategies and measures that were undertaken, were not sufficient for high growth levels.

These results can capture the situation existing in the world for the years 2000–2018, but the world has now entered a phase of energy transition, that includes changes in the electricity sector, where the use of renewables is more and more promoted [83]. This energy transition focuses on the use of new energy systems that are efficient and less harmful, but also has to take into consideration all the costs and risks related to the economy and the society that might result from such a transition and address them, so that this procedure will be sustainable [84].

The 13th Sustainable Development Goal, set by the United Nations in 2015, focuses on combating climate change, by promoting strategies and measures related to climate and by fostering resilience and adaptability. At the same time, the 8th SDG focuses on sustainable economic growth and on economic growth's disengagement from environmental degradation [85]; a relationship that was confirmed once again in this study. Even higher levels of GDP per capita are found to lead to higher levels of environmental degradation, but fossil fuels are considered to be essential, in order to cover current demand in electricity production. These results indicate that actions that minimize the exploitation of natural resources as well as the generation of pollutants and waste as GDP per capita grows and electricity demand is satisfied are necessary, in order to achieve the goals of sustainability.

In addition, the 7th SDG aims to reinsure that everyone in the world has access to reliable and sustainable energy sources, focusing on the reliance on clean fuels and on a higher share of renewables in world's final energy consumption [85]. The present study confirms once more the effects of fossil fuels on environmental degradation and the role of renewables on the improvement of environmental quality. At the same time, the study confirms the role of fossil fuels in boosting economic efficiency. These results highlight the urgent need for actions that promote energy transition and the targets of the 7th SDG, while taking into consideration all the necessary parameters, so that efficiency and growth are maintained.

In conclusion, the results of the present study, that highlight the relationships that existed among electricity production, economic growth and environmental degradation from the beginning of the 21st century, can be taken into consideration, along with the knowledge of new technologies, in order to fully understand those linkages in different income levels and undertake targeted actions that successfully promote energy transition, as well as the goals of sustainability. Different strategies should be implemented in countries of higher incomes, which have already achieved substantial socio-economic growth and have the necessary resources to invest in environmental protection and energy transition, while different measures should be implemented in lower-middle & low income countries, which have to focus mainly on their socio-economic development. Data shows that environmental degradation is caused primarily from higher incomes and the static model confirms that even higher income levels increase carbon dioxide emissions. Therefore, high income countries should focus on decreasing CO_2 emissions and on investing in environmental policies, while they should assist countries of lower incomes in their path of sustainable development, as should do countries of upper-middle income. In addition, and even though the EKC hypothesis is not confirmed for lower incomes and a positive relationship is found between economic growth and environmental degradation, it is suggested that lower-middle and low income countries should prioritize their socio-economic development, but without neglecting environmental protection, as the principles of sustainable development suggest.

Further analysis for specific countries is suggested, in order to identify with precision the linkages that exist between economic growth and carbon dioxide emissions in every place in the world separately, as well as more factors that have an impact on environmental degradation, while identifying the optimal shares of renewables and fossil fuels in electricity production. Such studies will be significantly important, in order to successfully promote energy transition with low socioeconomic costs and global sustainability.

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