What role of renewable and non-renewable electricity consumption and output is needed to initially mitigate CO2 emissions in MENA region?

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What role of renewable and non-renewable electricity consumption and output is needed to initially mitigate CO_2 emissions in MENA region?

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Abstract: This study attempts to explore the causal relationship between renewable and non-renewable electricity consumption, output and carbon dioxide (CO_2) emissions for 10 Middle East and North Africa (MENA) countries over the period of 1980–2009. The results from panel Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) show that renewable and non-renewable electricity consumption add in CO_2 emissions while output (real gross domestic product (GDP) per capita) exhibits an inverted U-shaped relationship with CO_2 emissions i.e. environment Kuznets curve (EKC) hypothesis is validated. The short-run dynamics indicate the unidirectional causality running from renewable and non-renewable electricity consumption and output to CO_2 emissions. In the long-run, there appears to be the bidirectional causality between electricity consumption (renewable and non-renewable) and CO_2 emissions. The findings suggest that future reductions in CO_2 emissions might be achieved at the cost of economic growth.

Keywords: Electricity consumption, Output, CO_2 emissions, MENA region

1. Introduction

Recently, the relationship between carbon dioxide (CO_2) emissions, real output[1] and energy consumption is largely studied, especially with combining both the literature of environmental Kuznets curve (EKC) and the existence of energy factor (e.g. Ang [1]; Apergis and Payne [2], [3]; Arouri et al. [4]; Lean Smyth [5]). In general, the EKC approach examines CO_2 emissions as a dependent variable in a function that considered economic growth and squared of economic growth as regressors (independent variables). According to this function, the specific hypothesis of the EKC indicates that when economic growth increases, emissions increase as well until a threshold level of economic growth is reached after which CO_2 emissions start to decline. This standard specification of an inverted U-shaped pattern between CO_2 emissions and economic growth is based on the presumption of the unidirectional causality running from economic growth (squared of economic growth) to CO_2 emissions. The presumption of this unidirectional causality has proposed many questions in studies based on the dynamics between economic growth and emissions (e.g. Akbostanci et al. [6]; Coondoo and Dinda [7]; Dinda and Coondoo [8]; Lee and Lee [9]). Also according to the EKC hypothesis, another issue related to the presence of omitted variable bias is presented. To take into account this omitted variable issue, several studies of Ang [1], Apergis and Payne [2], [3], Richmond and Kaufman [10], Soytas and Sari [11] and Soytas et al. [12] are based on the term of "quadratic EKC" including the energy factor.

According to our knowledge, now only the two works of Arouri et al. [4] and Farhani et al. [13] have still examined the log quadratic EKC equation for Middle East and North Africa (MENA) countries, but this equation has not been included renewable energy consumption. In addition, there are a few studies that have focused on the causal relationship between CO_2

[1] In economics, the term "output" may focus on many concepts and may also use many forms of variables such as Gross domestic product (GDP), income, economic growth, etc. This is related to the theory and the objective of the study in progress.

emissions as a dependent variable, renewable and/or non-renewable energy consumption and output (e.g., Apergis et al. [14]; Chiu and Chang [15]; Menyah and Wolde-Rufael [16]; Silva et al. [17])[2]. Thus, the present paper consists to examine the dynamic causal relationship between CO_2 emissions, renewable and non-renewable electricity consumption, and real Gross domestic product (GDP) per capita for the panel of MENA countries in order to mention the role of renewable energy consumption in carbon emissions reduction.

In addition, in spite of the increase in the number of countries that have established renewable energy development mechanisms for CO_2 emissions reduction, the environmental problems continue to worsen the growth of world economy (Chiu and Chang [15]). One of the most effective solutions that may turn the economy of the region into a sustainable path is generally based on the optimization between renewable and non-renewable energy consumption. According to the work of Farhani [18], the relatively renewable energy can be attributable not only from a single renewable resource, but also from a group of renewable resources known as hydro, wind, biomass, geothermal, solar, etc. To detect the interest of renewable energy use, powerful forces such as climate change, resource depletion and energy security can be presented and also affected the environment (Sadorsky [19]). Concerning climate change, this factor is recognized as one of the biggest threats and environmental catastrophes related to the rise of temperatures, sea levels, acidification of the world's oceans, etc. (For more details, see DeCanio [20]; Stern [21] and Reddy and Assenza [22]). In another way, climate change may present an impact on business activity via industry specific risks (such as regulatory and physical risks) and company specific risks (such as reputation, litigation and competitive risks) (For more details, see Labatt and White [23] and Sadorsky [24]). To mitigate these risks, International Energy Agency (IEA [25]) has indicated that renewable energy may offer

[2] For more details, see Section 3 of literature review.

significant opportunities for further growth, can facilitate the transition to a global sustainable energy supply by the middle of this century, and may also play a vital role in the mitigation of emissions.

Despite it is important to expose the direction of causality among variables (i.e., renewable and non-renewable electricity consumption, economic growth and CO_2 emissions; there is limited evidence available on analyzing the relationship among renewable and non-renewable electricity consumption and its implications for CO_2 emissions in the existing literature. Thus, the present study contributes in existing literature using a cross-sectional MENA region case. This consists to show how panel data analyses are able to capture the complexity of the economic environments, energy consumption, and histories of this region. Hence, few inferences drawn from previous studies provide only a general understanding of how the variables are broadly related, and the results cannot be generalized. For this purpose, we first investigate the causal relationship between CO_2 emissions, renewable and non-renewable electricity consumption and economic growth for 10 MENA countries over the period of 1980–2009. Then, we highlight the effect of renewable and non-renewable electricity consumption and economic growth on the environmental damage. Here CO_2 emissions have been taken as the environmental damage variable. The choice of CO_2 emissions as the environmental damage variable is primarily motivated by the fact that it is perhaps the most important of the green house gases leading to such consequences as global warming (Coondoo and Dinda [26]). This paper seeks also to estimate the long-run relationship using Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) techniques. The short-run dynamics are modeled appropriately in order to capture the long-run cointegrating relationship among variables. Finally, to supplement the findings of the long-run cointegration relationship, we perform Granger causality test to shed light on the causal relationship between economic growth and CO_2 emissions as well as between electricity (renewable and non-renewable) consumption and CO_2 emissions.

The remainder of the paper is organized as follows. Section 2 indicates the reason of the choice of MENA region and its recent trends. Section 3 presents literature review. Section 4 provides empirical methods. Section 5 summarizes and discusses the findings of this paper, while Section 6 concludes with policy implications.

2. MENA region: Choice and recent trends

The MENA region is chosen for several reasons. According to Farhani and Ben Rejeb [27], this region presents abundant human and natural resources, and also presents a large share of world petroleum production and exports. About two thirds of the world's proven crude-oil reserves exist in MENA region, with one quarter located in Saudi Arabia. About 15 percent of the world's total proven natural gas reserves exist in the Islamic Republic of Iran. The region also retains abundant non-fuel mineral and non-mineral resources. About one third of the world production of phosphate exists in Algeria, Morocco, Tunisia, Jordan and the Syrian Arab Republic. Morocco alone has more than 30 percent of the world phosphate rock and 40 percent of its phosphoric acid trade. The Islamic Republic of Iran possesses several natural resources such as potash, coal, ammonia and urea. Also Israel and Jordan possess potash, Mauritania has iron, and Qatar possesses ammonia and urea. In addition, it appears that Mauritania possesses copper and gypsum, Egypt and Sudan possess cotton, the Syrian Arab Republic possesses tobacco, and the Republic of Yemen possesses coffee. Furthermore, Al-Iriani [21] has mentioned that Gulf Cooperation Council (GCC)[3] countries are characterized by the possession of coasts and fishing grounds. Farhani [18] and the World Bank [29] proved

[3] The Gulf Cooperation Council (GCC) is a regional union of 6 countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

that most of MENA region's greenhouse gas (GHG) emissions are linked largely to the role of region's energy producers. In 2008, IEA indicated that total GHG emissions from fuel combustion in MENA were equal to 1.860 million metric tons of CO_2 equivalent. These emissions accounted for roughly 6.3 percent of the global emissions from fuel combustion. By 2010, the emissions from the region's power sector are estimated to have risen to 2.101 million metric tons of CO_2 equivalent.

According to Energy Information Administration (EIA [30]) report, Table 1-A reports the total renewable electricity net consumption measured in billion kilowatt-hours and the total CO_2 emissions from the consumption of energy measured in million metric tons for a sample of 10 MENA countries covering the annual period 2006–2010. For the total renewable electricity net consumption, all countries presented instability during this period. And the mean of total varies around 173 billion kWh. Tunisia is by far the biggest renewable electricity net consumer. Israel consumes the least. For the total CO_2 emissions from the consumption of energy, all countries have been trending upwards across time except Jordan, Morocco and Turkey. And the mean of total varies around 1275 million metric tons. Iran is by far the biggest emissions producer with Turkey and Egypt in a distant second. Sudan consumes the least energy.

Table 1-B reports total petroleum consumption, natural gas consumption, and total coal consumption measured in Quadrillion Btu. For the total petroleum consumption, all countries presented stability for this period. The total of all countries has been trending upwards across time, and the mean of total varies around 9 Quadrillion Btu. Iran is by far the biggest total petroleum consumer with Turkey and Egypt in a distant second. Sudan and Tunisia consume the least. For natural gas consumption, all countries have been trending upwards across time

except Tunisia, and the mean of total varies around 9 Quadrillion Btu. Iran is by far the biggest natural gas consumer. Sudan and Morocco consume the least. For the total coal consumption, all countries have been trending downwards across time except Turkey while Jordan, Sudan, Syria and Tunisia present stability across time. The mean of total varies around 173 Quadrillion Btu. Turkey is by far the biggest total coal consumer. Jordan, Sudan and Tunisia consume the least.

[Insert Table 1 here]

According to the main drivers of the present variables, Figure 1 shows plots in single graphs of CO_2 emissions, renewable and non-renewable electricity consumption and real GDP[4] for 10 MENA countries. For CO_2 emissions, all countries have been trending upwards across time although the strength of the trend varies by country. Tunisia is by far the biggest emissions producer with Turkey and Egypt in a distant second. Sudan consumes the least energy. The economic performance of all countries has been increasing along a fairly tight linear trend (without large downturns). Algeria is the largest economy while Israel, Jordan and Tunisia are the smallest. For renewable electricity consumption, all countries have been trending upwards across time although the strength of the trend varies by country except Algeria. Turkey is by far the biggest renewable electricity consumer with Egypt in a distant second. Algeria consumes the least renewable electricity. Concerning non-renewable electricity consumption, all countries have been trending upwards across time although the strength of the trend varies by country. Turkey is by far the biggest non-renewable electricity consumer and Algeria is the least renewable electricity consumer.

[4] All variables are "per capita" and in "natural log".

[Insert Figure 1 here]

3. Literature review

The relationship between the indicators of environmental degradation (such as Carbone dioxide (CO_2), Nitrogen oxides (NO_X), Sulfur dioxide (SO_2), etc.), energy (or electricity) consumption and economic growth is one of the important studies that needs to be explored in the literature review, but there are few studies that have focused on the causal relationship between CO_2 emissions, renewable and/or non-renewable electricity (or energy) consumption, and real output (e.g. Apergis et al. [14]; Chiu and Chang [15]; Menyah and Wolde-Rufael [16]; Silva et al. [17]).

Apergis et al. [14] examined the causal relationship between CO_2 emissions, renewable energy consumption, nuclear energy consumption and economic growth for a group of 19 developed and non-developed countries over the period of 1984–2007. They found a positive long-run relationship between CO_2 emissions and renewable energy consumption. The panel Granger causality test results suggest that in the short-run renewable energy consumption may not be able to reduce CO_2 emissions. Whereas, they have also mentioned that the lack of adequate storage technology to overcome intermittent supply problems may lead to biased results. As a result, Apergis et al. [14] concluded that producers of electricity have to rely on emissions generating energy sources to meet peak load demand.

Chiu and Chang [15] examined the impact of the renewable energy supply proportion and economic growth on CO_2 emissions reduction using the panel threshold regression (PTR)[5] model in all 30 member countries of the Organisation for Economic Co-operation and Development (OECD) over the period of 1996–2005. Their empirical results indicated that a

[5] The PTR model is treated in the works of Hansen [31]; Kourtellos et al. [32] and Wang and Lin [33].

single threshold effect appears to conclude two types of regime (lower regime and higher regime). Based on the estimated slope coefficients in each regime, they found that a renewable energy supply accounting for at least 8.39 percent of total energy supply might mitigate CO_2 emissions and might also help to resolve the problem between economic growth and CO_2 emissions.

Menyah and Wolde-Rufael [16] explored the causal relationship between CO_2 emissions, renewable and nuclear energy consumption and real GDP for the United States over the period of 1960–2007. The empirical results indicated the unidirectional negative causality running from nuclear energy consumption to CO_2 emissions. On the other hand, no causality was found between renewable energy consumption and CO_2 emissions, but CO_2 emissions Granger cause renewable energy consumption. Thus, Menyah and Wolde-Rufael [16] concluded that nuclear energy consumption might help to reduce CO_2 emissions, but renewable energy consumption did not lead to reach a significant contribution that might help to reduce CO_2 emissions.

In another work, Silva et al. [17] analyzed how an increasing share of Renewable Energy Sources (RES) on electricity generation may affect GDP and CO_2 emissions in a sample of four countries (USA, Denmark, Portugal, and Spain) over the period of 1960–2004. They used the Structural Vector Autoregressive (SVAR) approach in order to show the interactions among variables. This approach is used to predict the impacts of specific policy actions or important changes on the economy. Therefore, they have chosen four countries with rather different levels of economic development, social and economic structures, but with a specific effort of investment in RES. Empirically, the SVAR estimation showed that the increasing share of RES on electricity generation presented economic costs, except for the USA. In addition, there was also an evident decrease of CO_2 emissions only for the USA. This means that, the Danish, Portuguese and Spanish Governments are needed to complement RES support with other policies[6] in order to achieve environmental goals at least cost. As result, Silva et al. [17] concluded that rather different countries have similar goals to invest in the RES on electricity generation share; thus, the economic cost may disappear as these sources become economically competitive and then the RES will be cheaper (Bhutto and Karim [34]; Pimentel et al. [35]).

4. Methods

4.1 Model and data

This paper parallels the empirical approach taken by Ang [1], Halicioglu [36], Jalil and Mahmud [37], and Jayanthakumaran et al. [38] for the case of a single multivariate framework, and Apergis and Payne [2], [3], Arouri, et al. [4], Lean and Smyth [5] and Hossain [39] for a panel data framework.

To investigate the relationship between CO_2 emissions (C) per capita, electricity (renewable and non-renewable) consumption (E) per capita, real GDP (Y) per capita and squared real GDP (Y^2) per capita which is a synthesis of the EKC and energy consumption literature, the long-run model is given by the following equation:

$$C_{it} = \alpha_{it} + \beta_{1i}.E_{it} + \beta_{2i}.Y_{it} + \beta_{3i}Y_{it}^2 + \varepsilon_{it} \tag{1}$$

where α_{it} denotes the fixed country effect, ε_{it} denotes the stochastic error term, i = 1,…,N indicates country, and t = 1,…, T refers to the time period. The parameters β_{1i}, β_{2i} and β_{3i}

[6] The other policies may consider for example the demand-side management and the energy conservation.

are the long-run elasticities of CO_2 emissions per capita with respect to electricity (renewable and non-renewable) consumption, real GDP per capita and squared real GDP per capita, respectively. As for the expected signs in Eq. (1), one expects β_{1i} to be positive because a higher level of electricity (renewable and non-renewable) consumption should result in greater economic activity which stimulates CO_2 emissions per capita. Under the EKC hypothesis, the sign of β_{2i} is expected to be positive whereas a negative sign is expected for β_{3i}. The statistical insignificance of β_{3i} indicates a monotonic increase in the relationship between CO_2 emissions per capita and real GDP per capita. We realize that renewable electricity consumption (RE) and non-renewable electricity consumption (NRE) are two determining factors and have important impact on CO_2 emissions. According to the EKC hypothesis, the long-run relationship between CO_2 emissions per capita and real GDP per capita can be specified in non-linear logarithmic quadratic form as mentioned in Eq. (1).

Our approach consists to divide Eq. (1) into two separate models. In the first we examine the relationship between CO_2 emissions per capita, renewable electricity consumption, real GDP per capita and squared real GDP per capita, while in the second we replace the renewable electricity consumption by the non-renewable electricity consumption in order to investigate the relationship between CO_2 emissions per capita, non-renewable electricity consumption, real GDP per capita and squared real GDP per capita. This methodology is given by the following equations:

Panel A. $$LN(CO_2)_{it} = \alpha_{it} + \beta_{1i} LN(RE)_{it} + \beta_{2i} LN(GDP)_{it} + \beta_{3i} LN(GDP_{it}^2) + \varepsilon_{it} \tag{2}$$

Panel B. $$LN(CO_2)_{it} = \alpha_{it}^{'} + \beta_{1i}^{'} LN(NRE)_{it} + \beta_{2i}^{'} LN(GDP)_{it} + \beta_{3i}^{'} LN(GDP_{it}^2) + \mu_{it} \tag{3}$$

where CO_2 is the total carbon dioxide emissions from the consumption of energy measured in million metric tons; RE and NRE are respectively renewable and non-renewable electricity consumption measured in million kilowatt of hours (KWh); and real GDP per capita is the per capita real gross domestic product measured in millions of constant 2000 US$. The population series is used to convert all series into per capita. All variables are converted into natural logarithms (LN) for the usual statistical reasons. Annual data for real GDP per capita and CO_2 emissions are collected from World Bank Development Indicators (CD-ROM, 2011), while the annual data for electricity consumption (renewable and non-renewable) are collected from Energy Information Administration (EIA [40]). The present study covers the period of 1980–2009. We conduct empirical analysis for 10 MENA countries (Algeria, Egypt, Iran, Israel, Jordan, Morocco, Sudan, Syria, Tunisia, and Turkey). The panel data are chosen to include as many MENA countries as possible. Table 2 displays the summary of descriptive statistics associated with five variables in natural logarithms for each country.

[Insert Table 2 here]

4.2 Panel unit root tests

We propose two kinds of panel unit root tests (Breitung [41]; Im et al. [42, IPS]) in order to test the stationary properties of panel data.

4.2.1 Breitung [41] panel unit root test

Breitung [41] considered the following regression equation:

$$W_{it} = \alpha_{it} + \sum_{j=1}^{k+1} \beta_{ij} \Delta X_{i,t-j} + \varepsilon_{it} \tag{4}$$

where Δ is the first difference operator, W_{it} is the dependent variable, X_{it} is the independent variable, ε_{it} is a white-noise disturbance with a variance of σ^2, i =1, 2,..., N indicates country, and t = 1, 2,..., T indexes time. In Eq. (4), the test statistic of Breitung [41] assumed the following hypothesis: The null hypothesis is given by $H_0 : \sum_{j=1}^{k+1} \beta_{ij} - 1 = 0$, whereas the alternative hypothesis is given by $H_1 : \sum_{j=1}^{k+1} \beta_{ij} - 1 < 0$ and assumed that W_{it} is stationary. More precisely, Breitung [41] used the transformed vectors $w_i^* = AW_i = \left[W_{i1}^*, W_{i2}^*, ..., W_{iT}^* \right]'$ and $x_i^* = AX_i = \left[X_{i1}^*, X_{i2}^*, ..., X_{iT}^* \right]'$ in order to construct the following test statistic:

$$\lambda = \frac{\frac{1}{\sigma_i^2} \sum_{i=1}^{N} w_i^{*'} x_i^{*'}}{\sqrt{\frac{1}{\sigma_i^2} \sum_{i=1}^{N} x_i^{*'} A' A x_i^*}} \tag{5}$$

4.2.2 Im et al. ([42], IPS) panel unit root test

The IPS [42] test is based on the conventional ADF test for the following equation:

$$\Delta W_{it} = \alpha_i + \beta_i W_{i,t-1} + \gamma_i t + \sum_{j=1}^{k} \theta_{ij} \Delta W_{i,t-j} + \varepsilon_{it} \tag{6}$$

The IPS [42] test assumes the null hypothesis $H_0 : \beta_i = 0$ against the alternative $H_1 : \beta_i \prec 0$ for each individual *i*. The test is based on the test statistic $t_{\beta_i} = \hat{\beta}_i / \sigma(\hat{\beta}_i)$ (where $\hat{\beta}_i$ is the OLS estimate of β_i in Eq. (6) and $\sigma(\hat{\beta}_i)$ is its standard error). The IPS [42] test is also based on the mean group approach. This consists to use the average of the t_{β_i} statistics from Eq. (6) to perform the following $\bar{Z}$ statistic:

$$\bar{Z} = \sqrt{N}[\bar{t} - E(\bar{t})] / \sqrt{V(\bar{t})} \tag{7}$$

where $\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{\beta_i}$, and $E(\bar{t})$ and $V(\bar{t})$ are respectively the mean and the variance of each t_{β_i} statistic, and they are generated by simulations. $\bar{Z}$ converges to the standard normal distribution.

4.3 Panel cointegration tests

Given that each of the variables presents a panel unit root, we need then to check whether there is a long-run relationship between the variables using Pedroni ([43], [44]) and Kao [45] panel cointegration tests.

4.3.1 Pedroni, ([43], [44]) *panel cointegration tests*

Based on the residuals of the Engle and Granger [46] cointegration regression, Pedroni ([43], [44]) have studied a number of statistics (see Table 3). Assuming a panel of N countries, T observations and m regressors (X_m), the long-run model can be given as follows:

$$Y_{it} = \alpha_i + \lambda_i t + \sum_{j=1}^{m} \beta_{j,i} X_{j,it} + \varepsilon_{it} \quad t = 1,\ldots,T \quad i = 1,\ldots N \tag{8}$$

where $Y_{i,t}$ and $X_{j,i,t}$ are integrated of order one, i.e. I(1). Pedroni ([43], [44]) proposed seven statistics. Four of these statistics are based on *within-dimension* and called panel cointegration statistics, whereas the other three statistics are based on *between-dimension* and called group mean panel cointegration statistics (see Table 3).

[Insert Table 3 here]

Under null hypothesis, all seven tests indicate the absence of cointegration ($H_0 : \rho_i = 0 \;\; ;\forall i$), whereas the alternative hypothesis is given by $H_1 : \rho_i = \rho \prec 1 \;\; ;\forall i$ where ρ_i is the autoregressive term of the estimated residuals under the alternative hypothesis and it can be given by the following equation:

$$\hat{\varepsilon}_{i,t} = \rho_i \hat{\varepsilon}_{i,t-1} + u_{i,t} \tag{9}$$

Pedroni [43] concluded that all seven statistics have a standard asymptotic distribution and are based on the independent movements in Brownian motions when T and N $\rightarrow \infty$:

$$\frac{Z - \mu\sqrt{N}}{\sqrt{v}} \xrightarrow[N,T\rightarrow\infty]{} N(0,1) \tag{10}$$

where Z is one of the seven normalized statistics, and μ and v are tabulated in Pedroni [43].

4.3.2 Kao [45] panel cointegration test

Kao [45] proposed the following equation:

$$W_{i,t} = \alpha_i + \beta X_{i,t} + \varepsilon_{i,t} \tag{11}$$

where $W_{i,t} = \sum_{t=1}^{T} u_{i,t}$, $\mathrm{X}_{i,t} = \sum_{t=1}^{T} v_{i,t}$; $\forall t = 1,\ldots,T$, $i = 1,\ldots N$.

This test is based on the residual and variants of Dickey and Fuller [47] test and it is given by:

$$\hat{\varepsilon}_{i,t} = \rho\hat{\varepsilon}_{i,t-1} + \sum_{j=1}^{p} \varphi_j \Delta\hat{\varepsilon}_{i,t-j} + u_{i,t,p} \tag{12}$$

where ρ is selected when $u_{i,t,p}$ are not correlated under null hypothesis of the absence of cointegration. Then the statistic test can be given by:

$$ADF = \frac{t_{ADF} + \dfrac{\sqrt{6N}\hat{\sigma}_u}{2\hat{\sigma}_{0u}}}{\sqrt{\dfrac{\hat{\sigma}_{0u}^2}{2\hat{\sigma}_u^2} + \dfrac{3\hat{\sigma}_u^2}{10\hat{\sigma}_{0u}^2}}} \xrightarrow[under\ \ H_0]{} N(0,1) \tag{13}$$

where t_{ADF} is the t-statictic of ρ, and σ_{0u} comes from the covariance matrix $\Omega = \begin{bmatrix} \sigma_{0u}^2 & \sigma_{0uv} \\ \sigma_{0uv} & \sigma_{0v}^2 \end{bmatrix}$ of the bi-varied process $(u_{i,t}, v_{i,t})'$.

4.4 FMOLS and DOLS estimates

Although OLS estimators of the cointegrated vectors are super-convergents, their distribution is asymptotically biased and depends on nuisance parameters associated with the presence of serial correlation in the data (Pedroni [48] and Kao and Chiang [49]). Such existing problems in time series studies also arise for the panel data and tend to be more marked even in the presence of heterogeneity (For more details, see Kao and Chiang [49]). To carry out tests on the cointegrated vectors, it is consequently necessary to use methods of effective estimation. From various existing techniques, we will only mention two: FMOLS that initially suggested by Philips and Hansen [50] and DOLS of Saikkonen [51] and Stock and Watson [52]. In the case of panel data, Phillips and Moon [53] showed that OLS technique exhibits small sample bias, while FMOLS estimator appears to outperform both estimators. Similar results are got by Kao and Chiang [49] for the DOLS technique. This means that both OLS and FMOLS techniques exhibit small sample bias and that DOLS estimator appears to outperform both estimators. In addition, Kao and Chiang [49] also showed that FMOLS and DOLS techniques led to normally distributed estimators

4.4.1 FMOLS technique

The FMOLS technique is used by Pedroni [48] to solve the problem of endogeneity between regressors. Then he considered the following equation:

$$W_{i,t} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t} \tag{14}$$

He proposes that W_{it} and $X_{i,t}$ are cointegrated with slopes β_i, which β_i may or may not be homogeneous across i. In another way, he developed Eq. (14) as follows:

$$W_{i,t} = \alpha_i + \beta_i X_{i,t} + \sum_{k=-K_i}^{K_i} \gamma_{i,k} \Delta X_{i,t-k} + \varepsilon_{i,t} \tag{15}$$

Pedroni [48] also considered: $\xi_{i,t} = (\hat{\varepsilon}_{i,t}, \Delta X_{i,t})$ and $\Omega_{i,t} = \lim_{T\to\infty} E\left[\frac{1}{T}\left(\sum_{t=1}^{T}\xi_{i,t}\right)\left(\sum_{t=1}^{T}\xi_{i,t}\right)'\right]$ is the long-run covariance for this vector process which can be decomposed into $\Omega_i = \Omega_i^0 + \Gamma_i + \Gamma_i'$ where Ω_i^0 is the contemporaneous covariance and Γ_i is a weighted sum of autocovariance.

Thus,the FMOLS estimator can be given by:

$$\hat{\beta}^{*}_{FMOLS} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T}\left(X_{i,t} - \bar{X}_i\right)^2\right)^{-1}\left(\sum_{t=1}^{T}\left(X_{i,t} - \bar{X}_i\right)W^{*}_{i,t} - T\hat{\gamma}_i\right)\right] \tag{16}$$

where $W^{*}_{i,t} = W_{i,t} - \overline{W}_i - \frac{\hat{\Omega}_{2,1,i}}{\hat{\Omega}_{2,2,i}}\Delta X_{i,t}$ and $\hat{\gamma}_i = \hat{\Gamma}_{2,1,i} + \hat{\Omega}^{0}_{2,1,i} - \frac{\hat{\Omega}_{2,1,i}}{\hat{\Omega}_{2,2,i}}\left(\hat{\Gamma}_{2,2,i} + \hat{\Omega}^{0}_{2,2,i}\right)$.

4.4.2 DOLS technique

The DOLS technique was initially suggested by Saikkonen [51] for the time series case, and then adapted by Kao and Chiang [49] and Mark and Sul [54] for the panel data case. This technique consists to include advanced and delayed values of $\Delta X_{i,T}$ in the cointegrated relationship (see Eq. (15)) in order to eliminate the correlation between regressors and error terms.

Thus, the DOLS estimator is defined as follows:

$$\hat{\beta}^{*}_{DOLS} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T} Z_{i,t}Z_{i,t}'\right)^{-1}\left(\sum_{t=1}^{T} Z_{i,t}\tilde{W}_{i,t}\right)\right] \tag{17}$$

where $Z_{i,t} = \left[X_{i,t} - \bar{X}_i, \Delta X_{i,t-K_i}, \ldots, \Delta X_{i,t+K_i}\right]$ is vector of regressors, and $\tilde{W}_{i,t} = W_{i,t} - \overline{W}_i$.

4.5 Granger causality test

To perform Granger-causality test, a panel vector error correction model (VECM) based on the work of Pesaran et al. [55] is estimated. According to the study of Engle and Granger [46], two steps are employed to investigate the long-run and short-run dynamic relationships. The first step consists to estimate the long-run parameters in Eq. (1) and then get the residuals corresponding to the deviation from equilibrium. The second step consists to estimate the parameters related to the short-run adjustment. The resulting equation is used in conjunction with panel Granger causality testing as follows:

$$\begin{pmatrix} \Delta C_t \\ \Delta E_t \\ \Delta Y_t \\ \Delta Y_t^2 \end{pmatrix} = \begin{pmatrix} \phi_1 \\ \phi_2 \\ \phi_3 \\ \phi_4 \end{pmatrix} + \sum_{k=1}^{m} \begin{pmatrix} \theta_{1,1,k} & \theta_{1,2,k} & \theta_{1,3,k} & \theta_{1,4,k} \\ \theta_{2,1,k} & \theta_{2,2,k} & \theta_{2,3,k} & \theta_{2,4,k} \\ \theta_{3,1,k} & \theta_{3,2,k} & \theta_{3,3,k} & \theta_{3,4,k} \\ \theta_{4,1,k} & \theta_{4,2,k} & \theta_{4,3,k} & \theta_{4,4,k} \end{pmatrix} . \begin{pmatrix} \Delta C_{t-k} \\ \Delta E_{t-k} \\ \Delta Y_{t-k} \\ \Delta Y_{t-k}^2 \end{pmatrix} + \begin{pmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{pmatrix} .ECT_{t-1} + \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \end{pmatrix} \tag{18}$$

where the term Δ denotes first differences; ϕ_j (j = 1,2,3,4) represents the fixed country effect; k (k=1,…,m) is the optimal lag length determined by the Schwarz information Criterion (SC); λ_j (j=1,2,3,4) is the adjustment coefficient; $u_{j,t}$ (j=1,2,3,4) is the disturbance term assumed to be uncorrelated with zero means; and ECT_{t-1} is the estimated lagged error correction term derived from the cointegrating relationship and estimated via Eq. (19) as follows:

$$ECT_{t-1} = C_{t-1} - \hat{\alpha}_1 . E_{t-1} - \hat{\alpha}_2 . Y_{t-1} - \hat{\alpha}_3 Y_{t-1}^2 \tag{19}$$

5. Results and discussion

5.1 Panel unit root tests results

The results of Breitung [41] and IPS [42] panel unit root tests of each variable are reported in Table 4. The null hypothesis examines non-stationary. Our results presented the existence of unit root at level for all series. This means that each variable is integrated of order one, I(1).

[Insert Table 4 here]

5.2 Panel cointegration tests results

According to Eq. (2) and Eq. (3), the results of panel cointegration tests are given by Table 5. These equations showed the impact of electricity (renewable in Eq. (2) and non-renewable in

Eq. (3)) consumption per capita, real GDP per capita and squared real GDP per capita on CO_2 emissions per capita.

[Insert Table 5 here]

As shown in Table 5-A, the results of Pedroni's ([43], [44]) heterogeneous panel tests indicate that the null hypothesis of no cointegration can be rejected at the 5 percent significance level only for PP-stat and ADF-stat for both panel A and panel B. Kao's [45] residual cointegration test results for both panel A and panel B are reported in Table 5-B. The null hypothesis, which indicated that all variables are not cointegrated, can be rejected; thus, this means that all variables are cointegrated. Finally, we conclude that all variables are cointegrated at the 5 percent significance level, for both panel A and panel B.

5.3 FMOLS and DOLS estimates results

Table 6 displays FMOLS and DOLS long-run estimates results for Panel A and panel B, respectively. From the long-run equilibrium panels (A, B), we find that all coefficients are positive and statistically significant at 1 percent level.

From panel A, FMOLS estimates indicate that the elasticity of CO_2 emissions per capita with respect to real GDP per capita in the long-run is 0.132 – 0.023.LNGDP. In addition, a 1 percent increase in renewable electricity consumption per capita increases CO_2 emissions per capita by approximately 0.827 percent. However, DLOS estimates indicate that the elasticity of CO_2 emissions per capita with respect to the real GDP per capita in the long-run is 0.135 – 0.023.LNGDP. Moreover, a 1 percent increase in renewable electricity consumption per capita increases CO_2 emissions per capita by approximately 0.822 percent.

From panel B, FMOLS estimates indicate that the elasticity of CO_2 emissions per capita with respect to real GDP per capita in the long-run is 0.250 – 0.071.LNGDP. In addition, a 1 percent increase in real GDP per capita increases in non-renewable electricity consumption per capita increases CO_2 emissions per capita by approximately 0.692 percent. However, DOLS estimates indicate that the elasticity of CO_2 emissions per capita with respect to the real GDP per capita in the long-run is 0.254 – 0.070.LNGDP. Moreover, a 1 percent increase in non-renewable electricity consumption per capita increases CO_2 emissions per capita by approximately 0.698 percent.

[Insert Table 6 here]

5.4 Granger causality test results

For both Panel A and panel B, Table 7 summarizes the results of the short-run and long-run Granger-causality tests as previously outlined. The short-run dynamics suggests unidirectional causality running from renewable electricity consumption per capita (Panel A), non-renewable electricity consumption per capita (Panel B), real GDP per capita (squared real GDP per capita), respectively to CO_2 emissions per capita. With respect to the long-run dynamics, there are two bidirectional causality between renewable electricity consumption per capita (Panel A), non-renewable electricity consumption per capita (Panel B) and CO_2 emissions per capita. Per contra, a long-run causality running from electricity (renewable and non- renewable) consumption per capita and CO_2 emissions to real GDP per capita (squared of real GDP per capita) does not exist.

Our findings confirm the results of Ang [1] and Apergis and Payne [2], [3], which suggest that the degradation of the environment does not have a causal impact on economic growth. Instead, expansion of economic growth and energy consumption exert a causal impact on CO_2 emissions. One of the most interpretations is given by Farhani et al. [56], who mentioned that these results call for more attention in terms of environmental protection since environmental pollution may cause a negative externality to the economic energy through affecting human health and thereby reducing productivity. Our findings also indicate that the implementation of energy conservation policies has not inversely affected the long-term economic performance of MENA countries, but may positively affect the level of environmental pollution. Hence, the results imply that the economies of MENA region may be less sensible to energy shocks, which could adversely affect GDP growth. In the short run, the use of more electricity and real GDP is required to pollutant emissions. This problem can be solved by the development of energy conservation strategies.

[Insert Table 7 here]

6. Conclusions and policy implications

The present paper examines the short-run and long-run causal relationship between CO_2 emissions, renewable and non-renewable electricity consumption and economic growth for the panel of 10 MENA countries over the period of 1980–2009. Before testing for any causal relationship among the variables, panel unit root tests and panel cointegration tests analyses are applied. Two different panel unit root tests of Breitung [41] and IPS [42] have been used. These tests result that all the panel variables are integrated of order one. In addition, two different panel coitegration tests of Pedroni ([43], [44]) and Kao [45] have also been used. The results support that all the panel variables are cointegrated. In terms of Granger causality, unidirectional short-run causal relationships are found from electricity (renewable and non-renewable) consumption to CO_2 emissions per capita as well as from real GDP per capita to CO_2 emissions per capita; in the long-run, there is bidirectional causality between electricity (renewable and non-renewable) consumption per capita and CO_2 emissions per capita.

In terms of estimation, electricity (renewable and non-renewable) consumption per capita has a positive and statistically significant impact on CO_2 emissions per capita, whereas real GDP per capita exhibits a quadratic relationship. The results are supportive of the EKC hypothesis, which at first increase emissions, and then decrease it after a certain average GDP is attained. Hence, beyond a threshold level of real GDP, an increase in real GDP may actually reduce emissions as the demand for environmental quality increases as these economies grow. The finding results indicate that the environmental quality is not found to be good in respect of electricity consumption over time. This means that higher electricity consumption in the panel of MENA countries gives rise to more CO_2 emissions as a result the environment of MENA countries will be more polluted. This supports the results of Hossain [39].

In other words, the long-run as well as short-run energy consumption has significant positive impact on carbon dioxide emissions. This implies that due to expansion of the production of real GDP for rapid economic development, the MENA countries are consuming more electricity, which put pressure on the environment leading to more emissions; thus, it is very essential to apply some programs of pollution control actions to the whole panel in respect of electricity consumption. In another way, this implies that the absence of energy conservation policies in MENA countries, which is due to the level of economic development, these countries consume more electricity and then result a more polluted environment.

From these findings, we conclude that research and investment in clean energy should be an integral part of the process of controlling CO_2 emissions, as well as non-renewable energy contribute to mitigate emissions more than renewable energy because the economic cost of renewable energy sources seems to be expensive and economically competitive in the MENA region. According to other works, we can also mention that pollution can be reduced if governments: i) take into account globalization (Leitão [57]), and ii) improve the industrial sector by importing cleaner technology to attain maximum gain from international trade

(Farhani et al. [56]). This means that the inclusion of trade openness in the general model can mitigate emissions (Farhani et al. [56]; Halicioglu [36]; Jalil and Mahmud [37]; Jayanthakumaran et al. [38]; Shahbaz et al. [58]; Tiwari et al. [59]). Thus, for future research, we can focus on the inclusion of the trade openness and the index of globalization in order to attain a comprehensive impact of economic growth, renewable and non-renewable electricity consumption, trade openness and globalization on CO_2 emissions. This will provide new insights to policymakers in controlling environmental degradation.

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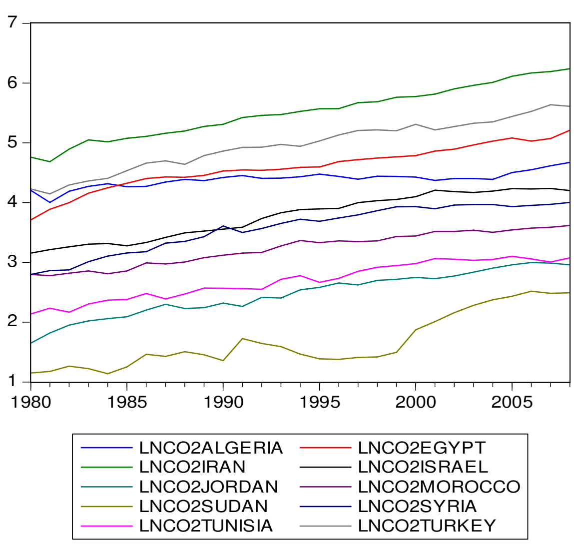
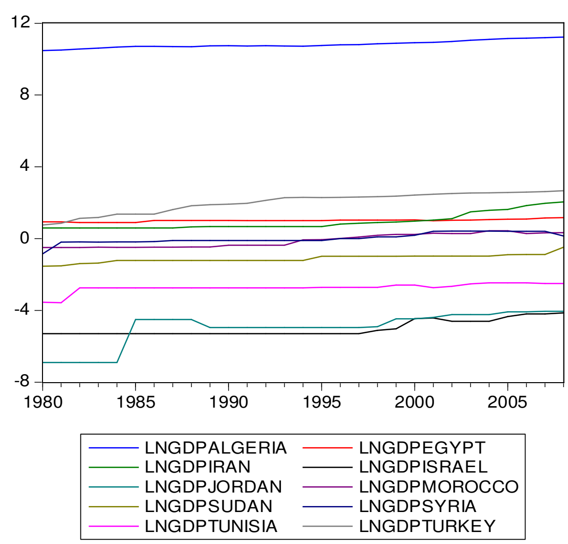
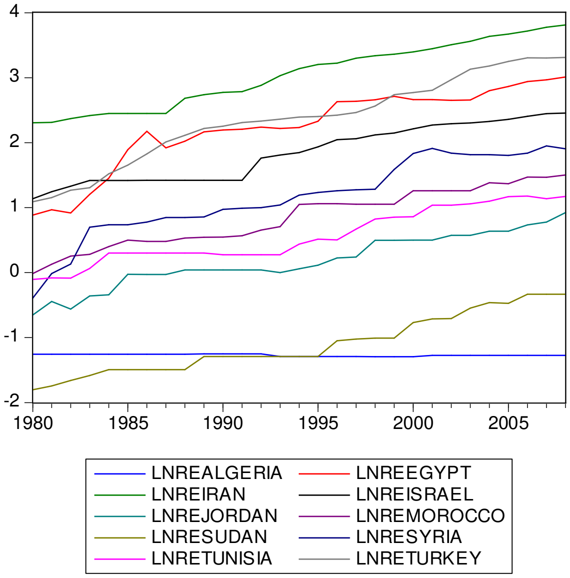
CO_2 emissions per capita (million metric tons)



Real GDP per capita (million of constant 2000 US$)



Renewable electricity consumption per capita (million KWh)



Non-renewable electricity consumption per capita (million KWh)

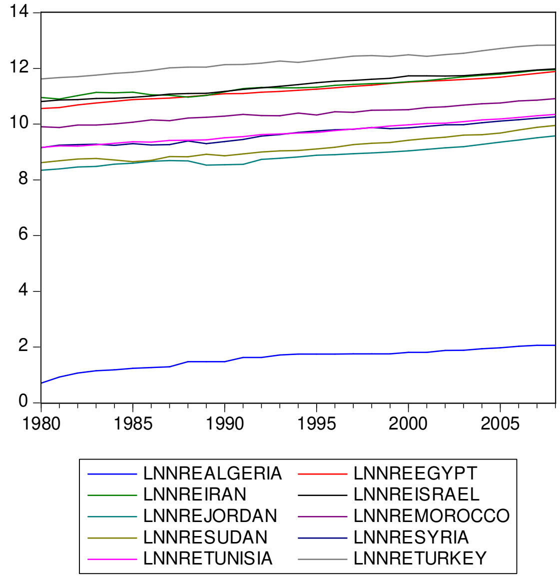


Figure 1. *Plots of CO_2 emissions per capita, renewable and non-renewable electricity consumption per capita and real GDP per capita (in natural log) for 10 MENA countries.*

Table 1

A. *Total renewable electricity net consumption (Billion kWh) and Total CO_2 emissions from the consumption of energy (million metric tons) for 10 MENA countries [a].*

	2006		*2008*		*2010*	
	EC	***CO_2***	***EC***	***CO_2***	***EC***	***CO_2***
Alegria	94.993	94.6480	97.648	106.832	110.904	110.901
Egypt	13.412	152.695	15.466	183.056	14.4010	196.547
Iran	18.208	477.037	5.1490	512.051	9.59400	560.335
Israel	0.0250	68.6000	0.0250	66.8500	0.14500	70.3210
Jordan	0.0590	20.0580	0.0720	19.2950	0.07000	19.0650
Morocco	1.1710	35.6710	1.2180	37.2300	4.09200	35.6620
Sudan	1.8660	12.3900	1.9580	12.1020	4.31400	13.7900
Syria	3.9060	52.0980	2.8400	54.8160	2.56600	63.1010
Tunisia	0.1290	21.2790	0.0690	21.6920	0.18900	18.7170
Turkey	44.176	250.957	34.165	272.900	55.3190	263.543
Total	177.94	1185.433	158.61	1286.824	182.647	1351.982

B. *Total non-renewable products consumption: Total petroleum consumption, Natural gas consumption, and Total coal consumption (Quadrillion Btu) for 10 MENA Countries [a].*

	2006			*2008*			*2010*		
	Petrol	***Gas***	***Coal***	***Petrol***	***Gas***	***Coal***	***Petrol***	***Gas***	***Coal***
Alegria	0.497	1.019	0.025	0.588	1.101	0.029	0.636	1.147	0.014
Egypt	1.354	1.019	0.033	1.498	1.515	0.031	1.479	1.663	0.030
Iran	3.382	4.054	2.872	3.544	4.449	1.949	3.578	5.392	2.579
Israel	0.517	0.035	14.65	0.456	0.052	13.06	0.505	0.132	13.91

Jordan	0.223	0.083	0	0.198	0.108	0	0.219	0.101	0
Morocco	0.360	0.002	0.135	0.428	0.021	0.123	0.483	0.021	0.016
Sudan	0.178	0	0	0.193	0	0	0.266	0	0
Syria	0.548	0.223	4	0.576	0.216	4	0.667	0.344	4
Tunisia	0.179	0.153	0	0.187	0.126	0	0.175	0.132	0
Turkey	1.372	1.145	108.9	1.374	1.338	108.9	1.301	1.384	112.5
Total	8.610	7.733	130.6	9.042	8.926	128.1	9.309	10.32	261.1

[a] *Source*: Energy Information Administration (EIA [30])

Table 2

Summary descriptive statistics, MENA countries, 1980–2009.

	LNCO$_2$	***LNRE***	***LNNRE***	***LNGDP***	***LNGDP²***
Mean	3.688610	-1.122200	1.271931	10.48342	111.1203
Median	3.728636	-0.675099	1.279535	10.64736	113.3668
Maximum	6.238425	2.663889	3.811296	12.83488	164.7341
Minimum	1.137926	-6.907755	-1.801810	8.345930	69.65454
Std. Dev.	1.197866	2.357981	1.253895	1.105606	23.18730
Skewness	-0.113305	-0.589155	-0.311964	-0.022309	0.144119
Kurtosis	2.293055	2.382836	2.642784	2.042098	2.120065
Jarque-Bera	6.659401	21.37910	6.245757	11.11143	10.35985
Probability	0.035804	0.000023	0.044030	0.003865	0.005628
Observations	300	300	300	300	300
Cross sections	10	10	10	10	10

Table 3

Pedroni ([43], [44]) panel cointegration tests.

A. Within-dimension (four statistics)

1. Panel v-Statistic

$$Z_v = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i}^{-2} \hat{\varepsilon}_{i,t-1}^{2} \right)^{-1}$$

2. Panel ρ -Statistic

$$Z_\rho = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i}^{-2} \hat{\varepsilon}_{i,t-1}^{2} \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i} \left(\hat{\varepsilon}_{i,t-1} \Delta \hat{\varepsilon}_{i,t} - \hat{\lambda}_i \right)$$

3. Panel non-parametric (PP) t-Statistic

$$Z_{pp} = \left(\tilde{\sigma}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i}^{-2} \hat{\varepsilon}_{i,t-1}^{2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i}^{-2} \left(\hat{\varepsilon}_{i,t-1} \Delta \hat{\varepsilon}_{i,t} - \hat{\lambda}_i \right)$$

4. Panel parametric (ADF) t-Statistic

$$Z_{ADF} = \left(\hat{S}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i}^{-2} \hat{\varepsilon}_{i,t-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{1,1i}^{-2} \hat{\varepsilon}_{i,t-1}^{*} \Delta \hat{\varepsilon}_{i,t}^{*}$$

B. Between-dimension (three statistics)

1. Group ρ -Statistic

$$\tilde{Z}_\rho = \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{\varepsilon}_{i,t-1}^{2} \right)^{-1} \sum_{t=1}^{T} \left(\hat{\varepsilon}_{i,t-1} \Delta \hat{\varepsilon}_{i,t} - \hat{\lambda}_i \right)$$

2. Group non-parametric (PP) t-Statistic

$$\tilde{Z}_{pp} = \sum_{i=1}^{N} \left(\hat{\sigma}^2 \sum_{t=1}^{T} \hat{\varepsilon}_{i,t-1}^{2} \right)^{-1/2} \sum_{t=1}^{T} \left(\hat{\varepsilon}_{i,t-1} \Delta \hat{\varepsilon}_{i,t} - \hat{\lambda}_i \right)$$

3. Group parametric (ADF) t-Statistic

$$\tilde{Z}_{ADF} = \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{S}_i^{-2} \hat{\varepsilon}_{i,t-1}^{*2} \right)^{-1/2} \sum_{t=1}^{T} \hat{\varepsilon}_{i,t-1}^{*} \Delta \hat{\varepsilon}_{i,t}^{*}$$

With:

a) $\hat{\lambda}_i = \frac{1}{T}\sum_{s=1}^{K}\left[1-\frac{s}{K_i+1}\right]\sum_{t=s+1}^{T}\hat{u}_{i,t}\hat{u}_{i,t-s}$ where $\hat{u}_{i,t} = \hat{\varepsilon}_{i,t} - \hat{\rho}_i\hat{\varepsilon}_{i,t-1}$;

b) $\hat{L}_{1,1,i}^{-2} = \frac{1}{T}\sum_{t=1}^{K}\hat{\eta}_{i,t}^2 + \frac{2}{T}\sum_{s=1}^{K}\left[1-\frac{s}{K_i+1}\right]\sum_{t=s+1}^{T}\hat{\eta}_{i,t}\hat{\eta}_{i,t-s}$ where $\hat{\eta}_{i,t} = \Delta Y_{it} - \sum_{m=1}^{M}\hat{b}_{m,i}\Delta X_{m,it}$;

c) $\tilde{\sigma}^2 = \frac{1}{N}\sum_{i=1}^{N}\hat{L}_{1,1i}^{-2}\hat{\sigma}_i^2$ where $\hat{\sigma}_i^2 = \hat{S}_i^2 + 2\hat{\lambda}_i$; and

d) $\hat{S}_i^2 = \frac{1}{T}\sum_{t=1}^{T}\hat{u}_{i,t}^2$; $\hat{S}_i^{*2} = \frac{1}{T}\sum_{t=1}^{T}\hat{u}_{i,t}^{*2}$ where $\hat{u}_{i,t}^{*} = \hat{\varepsilon}_{i,t} - \hat{\rho}_i\hat{\varepsilon}_{i,t-1} - \sum_{k=1}^{K_i}\hat{\rho}_{i,k}\Delta\hat{\varepsilon}_{i,t-k}$.

Table 4
Panel unit root test results.

Unit root test	***LNCO₂***	***LNER***	***LNNER***	***LNGDP***	***LNGDP²***
Breitung t-stat					
Level	1.17792	-0.23365	2.08680	2.046680	2.84038
	(0.8806)	(0.4076)	(0.9815)	(0.9797)	(0.9977)
First difference	-4.31541*	-9.43507*	-7.26170*	-7.60898*	-7.18590*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Im, Pesaran and Shin W-stat					
Level	-1.10277	0.37558	-1.61986	-0.33180	0.57239
	(0.1351)	(0.6464)	(0.0526)	(0.3700)	(0.7165)
First difference	-13.8130*	-10.4850*	-13.4563*	-12.3037*	-12.2537*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Decision	I(1)	I(1)	I(1)	I(1)	I(1)

Variables CO_2, RE, NRE, GDP and GDP² are expressed in natural logarithm (LN).
The null hypothesis of Breitung [41] and IPS [42] examines non-stationary.
* denotes statistical significance at the 1% level (Probabilities are presented in parentheses).
Lag selection (Automatic) is based on Schwarz Information Criteria (SIC).

Table 5
A. *Pedroni ([43], [44]) residual cointegration test (LNCO2 as dependent variable).*

	Method	***Statistic test***	***Prob.***	***Method***	***Statistic test***	***Prob.***
Panel A.	***Within-dimension***			***Between-dimension***		
	Panel υ-stat	1.546521	0.1207			
	Panel r-stat	0.056026	0.3983	Group r-stat	0.929523	0.2590
	Panel PP-stat	-2.863741*	0.0066	Group PP-stat	-5.471822*	0.0000
	Panel ADF-stat	-3.029278 *	0.0041	Group ADF-stat	-4.585199*	0.0000
Panel B.	***Within-dimension***			***Between-dimension***		
	Panel υ-stat	0.170634	0.3932			
	Panel r-stat	0.329180	0.3779	Group r-stat	0.347142	0.3756
	Panel PP-stat	-2.299058**	0.0284	Group PP-stat	-6.061502*	0.0000
	Panel ADF-stat	-1.963525**	0.0480	Group ADF-stat	-5.100706*	0.0000

B. *Kao[45]'s residual cointegration test (LNCO2 as dependent variable)*

		t-statistic	***Prob.***
Panel A. (with renewable electricity)	$LNCO_2$ **LNRE** LNGDP LNGDP²	-4.555005*	0.0000
Panel B. (with non-renewable electricity)	$LNCO_2$ **LNNRE** LNGDP LNGDP²	-3.901676*	0.0000

The null hypothesis indicates the absence of cointegration between variables.
* and ** indicate statistical significance at the 1 and 5% levels respectively.

Table 6

Panel FMOLS and DOLS long-run estimates results.

Panel FMOLS A. $LNCO_2$ = 2.644383 + 0.826996.**LNRE** + 0.132416.LNGDP - 0.011635.LNGDP²
[73.54317] [48.36097] [20.11648] [12.39657]
(0.0000)* (0.0000)* (0.0000)* (0.0000)*

Panel DOLS A. $LNCO_2$ = 2.658039 + 0.822315.**LNRE** + 0.134766.LNGDP - 0.011356.LNGDP²
[72.27591] [11.64897] [10.75296] [7.225807]
(0.0000)* (0.0000)* (0.0000)* (0.0000)*

Panel FMOLS B. $LNCO_2$ = -3.606620 + 0.692222.**LNNRE** + 0.250241.LNGDP - 0.035472.LNGDP²
[-5.560180] [11.64897] [10.75296] [7.225807]
(0.0000)* (0.0000)* (0.0000)* (0.0000)*

Panel DOLS B. $LNCO_2$ = -3.652797 + 0.697543.**LNNRE** + 0.253796.LNGDP - 0.035192.LNGDP²
[-5.376308] [46.19260] [19.57236] [11.66860]
(0.0000)* (0.0000)* (0.0000)* (0.0000)*

T-statistics are presented in brackets and probability values are reported in parentheses.
** indicates statistical significance at the 1% level.

Table 7
Granger causality test results.

	Dependent variable	***F-statistics* (Probabilities)**			***ECT$_{t-1}$*** **[t-stat]**
Panel A.		*ΔLNC$_t$*	*ΔLN**RE**$_t$*	*ΔLNY$_t$* (*LNΔY$_t^2$*)	
	ΔLNC$_t$	#	3.04976** (0.0456)	3.94812** (0.0392)	-0.236476** [-3.66325]
	*ΔLN**RE**$_t$*	0.82553 (0.3656)	#	0.73229 (0.4042)	-0.073782** [3.55297]
	ΔLNY$_t$ (*LNΔY$_t^2$*)	1.23496 (0.2722)	0.29833 (0.7980)	#	-0.040441 [-1.34287]
Panel B.		*ΔLNC$_t$*	*ΔLN**NRE**$_t$*	*ΔLNY$_t$* (*LNΔY$_t^2$*)	
	ΔLNC$_t$	#	2.94855** (0.0399)	2.83246** (0.0474)	-0.218521** [-4.92874]
	*ΔLN**NRE**$_t$*	0.79247 (0.2578)	#	0.93278 (0.6820)	-0.073546** [3.51097]
	ΔLNY$_t$ (*ΔLNY$_t^2$*)	1.35780 (0.3412)	0.33879 (0.8351)	#	-0.041921 [-1.22597]

T-statistics are presented in brackets and probability values are reported in parentheses.
** denotes statistical significance at the 5% level.