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The impact of renewable energy consumption to economic growth: A replication and extension of Inglesi-Lotz (2016)

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ABSTRACT

This study replicates and extends the results presented in a top-cited article in this journal, Inglesi-Lotz (2016), which analyzes the impact of renewable energy consumption to economic growth for the OECD countries by applying the ordinary least squares with fixed effect estimator on the data from 1990 to 2010. By using the same data and methods, this study first produces and compare empirical results with those reported in the original article. Then, it applies a set of new econometric methods on the same data to address heterogeneity in renewable energy and economic growth across the analyzed group of countries. The panel quantile regression estimation shows that the effect of renewable energy consumption on economic growth is positive for lower and low-middle quantiles; however, its effect becomes negative for middle, high-middle, and higher quantiles when renewable energy consumption is proxied by the absolute value. Furthermore, a negative impact of renewable energy on economic growth is observed in almost all quantiles when it is proxied by the share of renewable energy consumption to total energy consumption. These results greatly differ from those of the original study

1. Introduction

This study replicates estimates and extends the analysis from Inglesi-Lotz (2016), henceforth, I-L, which investigates the impact of renewable energy consumption to economic growth using the ordinary least square with fixed effect method in a panel data framework for the OECD countries over the period from 1990 to 2010. The results show that the impact of renewable energy consumption on economic growth is statistically significant, favoring the growth hypothesis. The original paper is a highly influential paper that has received around 250 citations in a short time listed as a top-cited article at the Energy Economics website. Moreover, it considers both the volume of renewable energy (absolute value) and its share in total energy consumption of each country, which has significant policy implications for future policies to promote renewable energies together with macroeconomic policies.

Analysis of the OECD countries is of crucial importance since these countries have declared their intentions to accomplish sustainable development goals and have made massive investments in green technologies that will replace fossil fuel consumption with renewable energy sources. Moreover, the OECD nations have a great influence on the green strategies of countries, and their policies are aimed to synchronize the member countries on sustainable development issues to promote green technologies, green jobs, and skills (OECD, 2011). The OECD/IEA joint report (OECD and IEA, 2011) emphasizes that promoting low-carbon energy technologies and eliminating fossil fuel subsidies are a priority for reducing emissions by half in 2050 globally. Also, the IEA, 2015 report states that OECD countries have critical importance in the world in terms of renewable energy sources. Therefore, the orientation of these countries to renewable energy sources means a global emission reduction, as well as a contribution to sustainable growth. Given the emphasis on the significance of renewable energy usage, these countries can be considered among the samples to generate conclusions and policy implications about renewable energy and economic growth relationship.

Energy consumption and economic growth nexus is a highly debated subject since the relationship between them suggests many significant policy implications. Despite the necessity of energy in generating welfare, it has an immense potential to deteriorate the environment (Álvarez-Herránz et al., 2017; Wadström et al., 2019). The use of fossil fuel entails various ecological problems, particularly in the forms of the decline of natural resources, and increasing carbon emissions over decades (Sinha et al., 2018). The production and usage of renewable energy are crucial for several reasons. First, high price volatility

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of fossil fuel creates various risks for energy poverty and price risks for oil-importing countries (Shahbaz et al., 2015, 2016). Second, the usage of non-renewable (renewable energy) exposes significant environmental resources like water, air, forests, etc., which could reduce the global income by about 25% (Stern, 2007). Third, energy security is another issue that encompasses risks for importing countries (Gnansounou, 2008; Hedenus et al., 2010), and renewable energy copes with both energy security and emission problems (Balsalobre-Lorente et al., 2018). Last, various agreements like Kyoto Protocol and Paris Agreement, oblige countries to impede their carbon emissions, thus renewable energy sources stand as the best means to ensure the goals of environmental protection, provision of energy security, and sustain growth.

A vast body of literature focuses on the impact of renewable energy on economic growth. Some studies in the first strand conclude that renewable energy consumption stimulates economic growth, such as Chontanawat et al. (2008) for developed OECD countries, Sadorsky (2009a) for G7 countries, Payne (2011) and, Dogan and Ozturk (2017) for the U.S., Lee and Chang (2008) for 16 Asian countries, Menyah and Wolde-Rufael (2010) for South Africa, Pao and Tsai (2010) for BRICS, Tiwari (2011) and Tang et al. (2016b) for India, Tang et al. (2016a) for Vietnam, Apergis and Payne (2010) for South American countries, Odhiambo (2010) for African countries, Arifin and Syahruddin (2011) for Indonesia, Al-Mulali and Sab (2012) for 30 Sub-Saharan African countries, Shahbaz et al. (2013) for China, and Apergis and Tang (2013) for 46 selected countries. Wadström et al. (2019) for Canada and Khan et al. (2020) for ASEAN countries. The second strand of literature finds no statistically significant impact of renewable energy on economic growth, such as Payne (2009), Bowden and Payne (2009) for the U.S., Menegaki (2011) for 27 European countries, and Ozcan and Ozturk (2019) for 17 emerging countries, Destek and Sinha (2020) for 24 OECD countries, Chen et al. (2020) for developed countries. The third part of the literature posits that renewable energy deteriorates economic growth due to high establishment costs of renewable energy infrastructure. This negative impact is reported by Ocal and Aslan (2013) for Turkey, Bhattacharya et al. (2016) for India, Ukraine, the U.S., and Israel.

The inconsistency of the findings, as summarized by Bourcet (2020), suggests that there is no clear consensus on the impact of renewable energy consumption on economic growth. The conflicting results due to the adoption of different periods, different methodologies, and different contexts. To analyze the renewable energy-growth nexus, some papers adopt conventional panel data methodologies; i.e. the Pedroni panel cointegration test, and various types of ordinary least squares (OLS), Sadorsky (2009a,b) Apergis and Payne (2010, 2011, 2012), Bowden and Payne (2009), Menyah and Wolde-Rufael (2010), Menegaki (2011), Yildirim et al. (2012), Apergis and Danuletiu (2014), Pao et al. (2014), Chang et al. (2015), Bhattacharya et al. (2016) and the original study I-L. On the other hand, recent literature focuses on panel quantile regression techniques to conclude the energy-growth nexus due to their superiority over the conventional methods in overcoming distributional heterogeneity (Sharif et al., 2020; Troster et al., 2018; Chen and Lei, 2018). Besides, Sim and Zhou (2015) mention that a quantile regression method can exploit interesting outcomes about the link between two variables, which is not usually exposed by OLS-type regressions. Overall, this paper both replicates the same empirical analysis of I-L's study and extends it by applying the panel quantile regression model due to Powell (2016) on the same dataset for the same country group.

2. Data, model, and methodology

Under I-L's study, this replication paper follows unit root, cointegration, and coefficient estimation test procedures, respectively. Moreover, it also expands the original work with different econometric approaches. So, the methodology part consists of two parts as replication and extension of the original study. As in the original study, Im-Pesaran-Shin (Im et al., 2003) unit root test is applied and results are checked by using Levin-Lin-Chu (LLC), Breitung, Fisher-ADF, and Fisher-PP panel unit root tests. Also, Pedroni's (1999, 2004) cointegration test and fixed effects OLS estimation are used for replication. Then, the results are expanded with a more current and novel method over models in Eqs. (1)-(4), originally stated by I-L:

$$\text{Model I}: GDP_{it} = \beta_0 + \beta_1 TRC_{it} + \beta_2 CAP_{it} + \beta_3 EMPL_{it} + \beta_4 RD_{it} + \varepsilon_{it} \quad (1)$$

$$\text{Model II}: GDP_{it} = \beta_0 + \beta_1 SRC_{it} + \beta_2 CAP_{it} + \beta_3 EMPL_{it} + \beta_4 RD_{it} + \varepsilon_{it} \quad (2)$$

$$\text{Model III}: GDPPC_{it} = \beta_0 + \beta_1 TRC_{it} + \beta_2 CAP_{it} + \beta_3 EMPL_{it} + \beta_4 RD_{it} + \varepsilon_{it} \quad (3)$$

$$\text{Model IV}: GDPPC_{it} = \beta_0 + \beta_1 SRC_{it} + \beta_2 CAP_{it} + \beta_3 EMPL_{it} + \beta_4 RD_{it} + \varepsilon_{it} \quad (4)$$

where the dependent variables *GDP* and *GDPPC* imply gross domestic product and gross domestic product per capita, respectively, are measured in constant US$ 2005. *TRC* is the total renewable energy consumption in kiloton of oil equivalent; *SRC* is the share of renewable energy consumption to total energy consumption; *CAP* is the capital stock (gross fixed capital formation in constant US$ 2005); *EMPL* is the number of employed people in a country; *RD* is the Research & Development expenditure in constant US$2005. The data are obtained from the study of I-L and also appended to this study. The dataset covers the period of 1990–2010 and includes 31 members of the OECD (Chile, Luxemburg, and Turkey are excluded because of data unavailability by the original study of I-L). Although the Table is not included in the original study, Table 1 presents some descriptive statistics regarding the dataset. It includes mean, smallest and largest values of data, standard deviation, and skewness statistics. Accordingly, the difference between the minimum and maximum values is sufficient. Standard deviations seem to be far from the mean values for all series. The fact that the skewness statistics, kurtosis statistics, and Jarque-Bera (J-B) statistics indicate that all datasets are not normally distributed, which suggests a new econometric approach to carry out this study. (See Table 2.)

First, the existence of dependence between cross-sections (countries) in the panel is analyzed using Pesaran's CD test (Pesaran, 2004), Friedman's test (Friedman, 1937), and Frees' test (Frees, 1995). Cross-sectional dependence, which occurs naturally in panel data studies and whose effect on coefficient estimation is undeniable, is a problem that needs to be explored to reveal the long-run relationship. Because the units in a panel dataset and within the scope of social sciences are interrelated (Sarafidis and Wansbeek, 2012). Ignoring the cross-sectional dependence reduces the efficiency of traditional methods and leads to statistical inference errors (Pan et al., 2015). Considering the cross-sectional dependence is important for the unit root, cointegration, and estimation of coefficients testing procedures used in the next stage. Second, the slope homogeneity test due to Pesaran and Yamagata (2008) are tested to check whether heterogeneity exists across countries for the analyzed dataset. Later, the cross-sectional augmented Dickey-Fuller (CADF) second-generation unit root test proposed by Pesaran (2007) taking into cross-sectional dependence and heterogeneity are applied. The CADF test assumes that the error term

Table 1
Descriptive statistics

	TRC	SRC	GDP	GDPPC	CAP	EMPL	RD
Mean	7.3	1.39	12.71	10.09	25.04	15.65	8.56
S.D.	1.31	1.07	1.51	0.37	1.54	1.52	1.71
Min	4.26	−1.95	8.74	8.9	20.93	11.82	4.15
Max	11.15	3.51	16.39	10.8	28.78	18.79	12.82
Skewness	0.27	−0.63	−0.11	−0.88	−0.11	−0.18	0.13
Kurtosis	2.88	2.82	3.16	3.33	3.10	3.07	2.96
Pr. (J-B test)	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: The values are in their natural logarithmic form.

Table 2
Results from slope homogeneity, cross-sectional dependence, and CADF panel unit root tests

	Model I		Model II		Model III		Model IV	
	value	*p*-value	value	p-value	value	p-value	value	p-value
CD-test	5.670	0.000	6.777	0.000	5.741	0.000	4.479	0.000
Δ_{adj}	21.263	0.000	21.683	0.000	24.755	0.000	25.249	0.000

	Levels				First-differences			
	Constant		Constant+Trend		Constant		Constant+Trend	
	Value	p-Value	Value	p-Value	Value	p-Value	Value	*p*-Value
GDP	−1.895	0.219	−2.053	0.938	−2.717	0.000	−2.935	0.000
GDPPC	−1.705	0.624	−1.760	1.000	−2.522	0.000	−2.783	0.000
TRC	−2.218	0.000	−2.481	0.153	−2.997	0.000	−3.152	0.000
SRC	−2.053	0.046	−2.372	0.354	−2.875	0.000	−3.176	0.000
CAP	−2.197	0.006	−2.235	0.673	−3.136	0.000	−3.223	0.000
EMPL	−1.397	0.981	−2.190	0.763	−2.671	0.000	−2.628	0.000
RD	−1.989	0.094	−1.858	0.997	−2.492	0.000	−2.906	0.000

consists of two parts common to all series and specific to each series. The Pesaran (2007) panel unit root test does not require the estimation of factor loading to eliminate cross-sectional dependence. Specifically, the usual ADF regression is augmented to include the lagged cross-sectional mean and its first difference to capture the cross-sectional dependence that arises through a single-factor model. The null hypothesis is a unit root. Third, after determining the degree of integration of the series, the cointegration relationship is investigated using Westerlund (2007) procedure, which is robust to cross-sectional dependence and heterogeneity and prevents to the common factor restrictions. Fourth, the quantile regression developed by Powell (2016) is adopted for the models I-IV in (Eqs. (1)-(4)).

Quantile regression analysis is used when independent variables potentially have varying effects at different points in the conditional distribution of the dependent variable. Thus, heterogeneous effects neglected in average regression techniques are considered (Bitler et al., 2006). There is growing interest in the literature on panel quantile with additive fixed effects (Koenker, 2004; Harding and Lamarche, 2009; Lamarche, 2010; Canay, 2011; Kato et al., 2012), but this approach is inefficient in terms of estimating a large number of fixed effects and considering incidental parameters problems when T is small. Powell's (2016) quantile regression approach eliminates this problem and allows nonadditive fixed effects. The panel quantile regression form with fixed effects as follows:

$$y_{it} = \alpha_i + \beta(q)x'_{it} + u_{it} \tag{5}$$

where i denotes the number of countries and t is the time dimension. The variable y is the dependent variable, while the vector x includes all independent variables. q denotes the quantile ($0 < q < 1$) of the conditional distribution, α shows the presence of fixed effects. The impact of the x drivers is allowed to depend upon the quantile q, but the fixed effects α_i does not. To estimate this model, Koenker (2004) suggests a regularization or shrinkage of these individual effects toward a common value by considering a penalty. This method, called penalized quantile regression, takes the following form:

$$min_{\alpha\beta} \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{i=1}^{N} w_k \rho_{Tk}(y_{it} - \alpha_i - \beta(\tau_k)x_{it}^T) + \lambda P(\alpha) \tag{6}$$

where $p(\alpha) = \sum_{i=1}^{N}|\alpha_i|$ is the penalty considered. *i*, *T*, and *K* denotes the index for countries, the index for the number of observations per country, and is the index for quantiles, respectively. The weights w_k control the relative influence of the quantiles. λ implies the tuning parameter. Despite the robust methodological basis of quantile regression with additive fixed effects, the Powell's (2016) technique demonstrate to be more useful in predicting a large number of fixed effects in a quantile framework and considering incidental parameters probability in case of T is small. The model is constructed as follows:

$$Y_{it} = \sum_{j=1}^{8} D'_{it}\beta_j(U^*_{it}) \tag{7}$$

where Y_{it} is GDP for model 1 and model 2, being GDP per capita for model 3 and model 4. β_j are parameters of independent variables, while D_{it} implies the set of independent variables (these are total renewable energy consumption, capital stock, employment level and R&D expenditure for model 1 and model 3; and these are the share of renewable energy consumption, capital stock, employment level and R&D expenditure for model 2 and model 4). U^*_{it} denotes the error term. For the $D_{it}'\beta(\tau)$ is strictly increasing in τ, and for the τ^{th} quantile of Y_{it} The quantile regression relies on the conditional restriction:

$$P(Y_{it} \le D'_{it}\beta(\tau)|D_{it}) = \tau \tag{8}$$

Powell's (2016) estimator (QRPD) based on both a conditional restriction and an unconditional restriction:

$$\begin{aligned} &P(Y_{it} \le D'_{it}\beta(\tau)|D_{it}) = P(Y_{it} \le D'_{is}\beta(\tau)|D_{it}) \\ &\beta(Y_{it} \le D'_{it}\beta(\tau)) = \tau; D_i = (D_{it}, \ldots, D_{iT}) \end{aligned} \tag{9}$$

Moreover, Powell (2016) presents the estimation with instrumental variables. They are suggested as $Z_{it} = (Z_{i1}, \ldots, Z_{iT})$, and are included in the model using the generalized method of moments (GMM) as follows:

$$\begin{aligned} \hat{g}(b) &= {}^1/_N \sum_{i=1}^{N} g_i(b) \text{ with } g_i(b) \\ &= {}^1/_T \left\{ \sum_{i=1}^{T} \left(Z_{it} - \left({}^1/_T \sum_{i=1}^{T} Z_{it} \right) \right) [1(Y_{it} \le D'_{it}b)] \right\} \end{aligned} \tag{10}$$

The parameter set can be presented as:
$\beta \equiv \left\{ b | \tau - {}^1/_N \le {}^1/_N \sum_{t=1}^{N} (Y_{it} \le D'_{it}b) \le \tau \right\}$ for all t, and estimation of each parameter as:

$$\hat{\beta}(\tau) = \ arg \ \underset{\smile}{min}_{b \in g}\ \hat{g}(b)' \hat{A} \hat{g}(b) \tag{11}$$

where $\hat{A}$ is the weighting matrix.

3. Replication results

This study starts the empirical exercise by applying some panel unit root tests as in the original study. (Results are reported in Table A.1 in the Appendix). First of all, we obtain the same results as in I-L. On the

Table 3
Results from Pedroni panel cointegraion test.

	Model I		Model II		Model III		Model IV	
	Panel	Group	Panel	Group	Panel	Group	Panel	Group
i) Original study I-L								
V-stat	−1.368		0.789		2.584[a]		1.475[b]	
p-stat	3.924	5.968	4.825	6.376	4.594	6.873	4.312	6.581
PP-stat	−0.995	−4.616[a]	−2.416[a]	−6.398[a]	−1.404[b]	−4.401[a]	−2.750[a]	−5.468[a]
ADF-stat	−1.492[b]	−3.175[a]	−1.822[b]	−4.637[a]	−1.290	−2.321[b]	−1.500[c]	−2.901[a]
ii) Our Estimation								
V-stat	−1.361		−1.390		−0.175		−0.645	
p-stat	3.929	5.968	3.788	5.636	3.165	5.434	3.339	5.410
PP-stat	−0.974	−4.601[a]	−1.143	−5.229[a]	−1.819[c]	−5.539[a]	−1.801[b]	−5.670[a]
ADF-stat	−1.475[c]	−3.179[a]	−2.078[b]	−4.071[a]	−1.477[c]	−3.535[a]	−2.034[b]	−4.252[a]

Note: [a], [b], [c] denote 1%, 5% and 10% significance level, respectively.

other hand, these are among first-generation unit root tests. By applying the Pesaran's (2004) cross-sectional dependence test, and Pesaran and Yamagata's (2008) slope homogeneity test (Δ_{adj}), this study suggests the use of a second-generation unit root test, which consider both issues.

Table 2 shows the outcome from a CD-test, a slope homogeneity test, and the CADF unit root test. The existence of cross-sectional dependency is confirmed for all models. Pesaran and Yamagata's (2008) slope homogeneity test results show that the null hypothesis is rejected. This means that the slope coefficients are heterogeneous. Similarly, the null hypothesis of no cross-section dependence for analyzed variables across the OECD nations can be rejected. According to the unit root test, all of the variables have unit root in the model with a trend. *TRC*, *SRC*, *CAP*, and *RD* are stationary at levels in model without a trend. In general, it is a fact that all series are I(1). Even though statistical significance slightly differs across unit root tests, the non-stationarity at levels is similar to I-L.

After the exercise of the above-mentioned tests, the next is to perform Pedroni's (1999, 2004) cointegration test following I-L's study. Results from the original study and our estimation are reported in Table 3. Even though some statistics are slightly different, the main conclusion stays the same. However, as it is the case in the panel unit root test, the Pedroni cointegration test is the first-generation approach; thus, a second-generation cointegration is recommended. The result from Westerlund's (2007) cointegration test which considers not only heterogeneity but also cross-sectional dependence is reported in Table 4. Neither of the models yields a cointegration. It is a controversial outcome to those reported in Table 3.

Given the absence of established cointegration (long-run relationship), a solution to investigate the impact of renewable energy on economic growth is to use the first-differences of the dataset (Albulescu et al., 2019). Although analysis with the first-difference of variables is considered an alternative, it is understood that the results are no longer similar to I-L. Because, as in the original study, the assumptions of Gaussian errors may not be held in terms of fixed OLS panel regressions, as well as in cases where the dependent variable, i.e. economic growth, exhibits skewed distributions. Since heterogeneity exists across countries for the analyzed variables and the data is not normally distributed, we prefer the application of the panel quantile regression method for the sake of replication as it takes into account heterogeneity of the sample and is robust to non-normal distribution of the dependent variable. Thus, the importance of renewable energy consumption for growth may be explained by emphasizing the differences in terms of the economic growth of the sample group (OECD countries).

Table 4
Results from Westerlund (2007) panel cointegration test.

	Model I		Model II		Model III		Model IV	
	Value	p-Value	Value	p-Value	Value	p-Value	Value	p-Value
Gt	−1.305	1.000	−1.460	0.998	−1.296	1.000	−1.548	0.990
Ga	−2.060	1.000	−2.485	1.000	−1.914	1.000	−2.927	1.000
Pt	−6.292	0.984	−7.207	0.922	−5.535	0.997	−6.455	0.978
Pa	−2.102	0.999	−2.473	0.997	−2.254	0.998	−2.897	0.993

4. Main findings- a panel quantile analysis

I-L's study estimates the impact of renewable energy (RE) consumption on economic welfare concluding for its positive and statistically significant impact. The author does it through panel data techniques concluding for the direct impact of RE in both the environment and economic conditions of the OECD countries from 1990 to 2010.[1] Ordinary least-squares methods (OLS) cannot provide useful information regarding the heterogeneous effects of the dependent variable (Bitler et al., 2006; Albulescu et al., 2019). When variables have varying or different effects in the conditional distribution of the dependent variable, quantile regression analysis is more suitable (Albulescu et al., 2019; Sarkodie and Strezov, 2019). Additionally, this method allows us to observe the non-linearity impacts of regressors on the dependent variable of interest. Provided our replicating study uses a sample of OECD countries that are fundamentally heterogeneous regarding their income levels, it is wiser to analyze the disparities considering summary point estimates for coefficients rather than to focus on an average effect.

Results from Powell's (2016) panel quantile regression are reported in Table 5 when GDP is the dependent variable - Model I & II, and in Table 6 when GDPPC is the dependent variable -Model III & IV. Several findings are highlighted. First, when renewable energy consumption is proxied by total consumption or absolute value, the effect is positive for lower and low-middle quantiles; however, the effect of renewable energy on the growth becomes negative for middle, high-middle and higher quantiles. Thus, in low-income OECD countries (like Estonia, Iceland, Slovak, Slovenia, and Luxembourg), renewable energy has a positive impact over GDP, while in high-income countries (like considering 2010 data, US, UK, Japan, Italy, Germany, and France) renewable energy exerts a negative influence over GDP. Second, when renewable energy consumption is proxied by the share of renewable energy consumption to total energy consumption it is denoted a negative impact of RE share over GDP even if not statistically significant, except in the 50th and 90th quantiles. Results differ from those of I-L's study in the positive impact identified. Finally, gross capital formation, employment,

[1] The results from the Powell's quantile regression by using an updated dataset are reported in A.2 and A.3 in the Appendix. It should be noted that the data on the same analyzed variables for the OECD countries are available up to 2016 from the same sources as in I-L; however, the base-year (reference year) is switched from 2005 to 2015 and the renewable energy data is modified for some years, i.e. 1990 and 1991, for countries. Thus, this study does not prefer to use the results from the updated dataset for comparison with I-L.

Table 5
Results from Powell's (2016) panel quantile regression- GDP as dependent variable.

Quantile		Model I: dGDP				Model II: dGDP			
		dTRC	dCAP	dEMPL	dRD	dSRC	dCAP	dEMPL	dRD
5	Coeff.	0.016[b]	0.209[a]	0.189	0.04	−0.013	0.228[a]	0.159	0.038
	z-stat	2.52	3.18	0.52	0.72	−0.40	3.83	0.58	0.60
10	Coeff.	0.001	0.217[a]	0.127	0.072[b]	−0.001	0.155[a]	0.145	0.035[c]
	z-stat	0.44	5.65	0.94	2.21	−0.03	6.68	0.90	1.86
20	Coeff.	0.003	0.226[a]	0.089[a]	0.067[a]	−0.002	0.226[a]	0.070	0.060
	z-stat	0.62	7.22	2.84	2.83	−0.50	7.48	1.55	1.50
30	Coeff.	0.007	0.224[a]	0.115	0.046[b]	−0.001	0.207[a]	0.126	0.044
	z-stat	0.94	5.43	1.19	2.30	−0.27	4.62	1.35	1.62
40	Coeff.	0.006	0.206[a]	0.151	0.051[a]	−0.004	0.145[b]	0.113	0.027[c]
	z-stat	0.66	6.15	1.35	3.67	−0.81	2.52	1.37	1.65
50	Coeff.	−0.002	0.203[a]	0.158[c]	0.058[a]	−0.007[b]	0.144[a]	0.151[c]	0.031
	z-stat	−0.29	3.70	1.93	3.77	−2.23	4.15	1.73	1.63
60	Coeff.	−0.001	0.130[a]	0.191	0.026	−0.004	0.147[a]	0.177[c]	0.021
	z-stat	−0.14	2.95	1.42	0.85	−0.55	3.70	1.77	1.06
70	Coeff.	−0.004	0.182[a]	0.170[b]	0.048[c]	−0.007	0.140[a]	0.167[c]	0.012
	z-stat	−1.09	6.89	2.51	1.93	−0.32	4.05	1.85	0.63
80	Coeff.	−0.003	0.167[a]	0.221[b]	0.029	−0.013	0.160[a]	0.219[a]	0.020
	z-stat	−0.28	3.56	2.39	0.74	−1.17	5.13	2.95	0.76
90	Coeff.	−0.014[a]	0.156[a]	0.232[a]	0.015	−0.014[a]	0.156[a]	0.306[b]	0.013
	z-stat	−4.84	4.19	2.89	0.71	−3.61	3.66	2.23	0.52
95	Coeff.	0.004	0.126[a]	0.335	−0.008	−0.013	0.162[a]	0.295[c]	−0.023
	z-stat	0.39	7.15	1.17	−0.40	−1.53	5.95	1.71	−1.42

Note: [a], [b], [c] denote 1%, 5% and 10% significance level, respectively.

and research and development expenditure (except in the 95th quantile for R&D) contribute positively to high-income levels as highlighted in the growth literature. This outcome is consistent with that of the original study.

Similar conclusions can be undertaken from GDPPC except considering the share of renewable energy. In Table 6 we may observe that in absolute terms, renewable energy consumption has a positive impact over GDPPC in low to middle quantiles or low to middle-income countries, but when considering the share of renewable energy impact over GDP in per capita terms we observe that up to the 20th quantile the impact remains positive. From the 30th quantile up to the 90th quantile, the impact remains negative, inducing a negative effect of the increase of the share of renewable energy consumption over GDPPC. Furthermore, we still confirm the positive effect generated by employment, capital stock, and research and development expenditure over GDPPC.

Despite the empirical findings regarding Tables 5 and 6 we need to highlight that the group of countries composing the high- and low-income countries as measured by GDP differs from those concerning GDP per capita. In the situation where the dependent variable is GDPPC, those countries, as of 2010, with higher GDPPC were Luxembourg, New Zealand, US, Switzerland, and the Netherlands, whereas those with lower GDPPC in 2010 were Turkey, Mexico, Chile, Estonia, and Hungary. Therefore, results are robust in terms of GDP and GDPPC for total energy consumption but differ slightly when considering the share of renewable energy consumption to total energy consumption when the impact is over GDPPC, for very low per capita

Table 6
Results from Powell's (2016) panel quantile regression-GDPPC as dependent variable

Quantile		Model III: dGDPPC				Model IV: dGDPPC			
		dTRC	dCAP	dEMPL	dRD	dSRC	dCAP	dEMPL	dRD
5	Coeff.	0.013	0.129[a]	0.305[a]	0.022	0.009	0.214[a]	0.118[b]	0.047[c]
	z-stat	0.71	4.34	3.83	0.95	0.63	4.11	2.42	1.69
10	Coeff.	0.012	0.229[a]	0.146	0.032	0.002	0.226[a]	0.108	0.035
	z-stat	0.47	3.52	0.77	0.77	0.30	4.19	0.63	1.43
20	Coeff.	0.006[b]	0.241[a]	−0.010	0.053[b]	0.002	0.245[a]	−0.014	0.052[c]
	z-stat	2.28	3.99	−0.07	2.32	0.30	6.03	−0.12	1.70
30	Coeff.	0.002	0.141[a]	0.077	0.015	−0.004	0.146[a]	0.081	0.015
	z-stat	0.22	3.65	0.61	0.64	−0.42	4.40	0.61	0.66
40	Coeff.	0.001	0.151[a]	0.071	0.021	−0.002	0.150[a]	0.077	0.022
	z-stat	0.11	4.85	0.85	1.49	−0.31	5.46	0.92	1.35
50	Coeff.	0.003	0.177[a]	0.083	0.023	0.000	0.159[a]	0.084	0.025
	z-stat	0.35	4.20	1.06	1.59	−0.08	2.59	0.97	0.89
60	Coeff.	−0.001	0.173[a]	0.101	0.029	−0.005	0.152[a]	0.112	0.014
	z-stat	−0.14	2.47	0.64	1.10	−1.09	2.95	0.80	0.52
70	Coeff.	−0.003	0.136[a]	0.078	0.030	−0.010[b]	0.176[a]	0.126	0.025
	z-stat	−0.28	3.83	1.01	1.53	−2.26	4.89	1.55	1.20
80	Coeff.	−0.003	0.133[a]	0.171	0.017	−0.012	0.187[a]	0.193	0.037
	z-stat	−0.38	3.06	1.52	0.90	−1.59	3.16	1.33	1.25
90	Coeff.	−0.009[b]	0.164[a]	0.245	0.024	−0.009[b]	0.165	0.250	0.021
	z-stat	−2.14	2.50	0.96	0.55	−2.21	1.62	0.68	0.49
95	Coeff.	0.013	0.137	0.438[c]	−0.007	0.010	0.168	0.462	−0.002
	z-stat	0.25	1.08	1.71	−0.13	0.07	0.83	0.73	−0.02

Note: [a], [b], [c] denote 1%, 5% and 10% significance level, respectively.

income countries (up to the 20th quantile). However, we need to bear in mind that the set of countries of high income, low income, high per capita income and low per capita income differ, and the analysis should be made with caution.

Powell's (2016) approach; therefore, while providing unconditional quantile treatment effects allowing us to include multiple control variables without influencing the results, allowed us to reach different conclusions as compared to I-L methodology. If it is true that renewable energy consumption drives economic growth, it does that but for low, low-middle, and middle-income countries. The same is not true when considering the share of renewable energy consumption since our results pointed for a negative impact, except using the share impact in very low per capita income countries within the set of OECD countries under analysis, thus contradicting I-L findings for the overall set. Results, therefore, reveal that GDP and GDPPC are heterogeneous among these countries, but the impact of renewable energy over both types of income becomes homogeneous for different income levels of groups of countries within the OECD.

The quest to increase renewable energy consumption in low and low-middle income countries increases GDP and GDPPC on these but imposes higher costs and a turning point in economic development. As opposed to the original study, our findings do not evidence the stimulating role of renewable energy consumption in the economic growth of all OECD countries. It has a positive effect which differs by the income level of the country under analysis. This empirical evidence suggests that countries with lower to low-middle income, both in absolute GDP or per capita GDP terms, should increase investment in renewable energy sectors. Thus, they should plan for development in renewable energy for sustainable energy growth.

However, when we analyze the results of the impact of the share of renewable energy consumption over total energy consumption it is clear the negative impact over GDP and GDPPC, except in the latter considering very low per capita income countries (lowest quantiles). Thus, results seem to highlight the high dependence of richer countries over fossil fuel, stimulating their economic growth and development. Then, strategies to increase the share of renewable energy consumption into total energy consumption would simply lower both GDP and GDPPC.

5. Conclusion and discussions

This study is an attempt to replicate and extend the study Inglesi-Lotz (2016) or (I-L). First of all, this study obtains the same outcome and conclusion that renewable energy leads to economic growth while the same methods are applied to the same data as in I-L. However, while replicating the results of I-L using Powell's (2016) novel quantile regression technique, this study finds evidence against the main conclusion of I-L's study. Results from quantile regression estimation reveal that renewable energy consumption leads to negative economic growth as measured through GDP in high-income OECD countries whereas renewable energy consumption seems to lead to higher growth in lower to low-middle income nations. But these results are observed when we consider the total consumption of renewable energy because when using the share of renewable energy consumption, it is noticed a negative impact on growth. Concerning per capita growth, those with higher levels observe a negative impact of renewable energy consumption in absolute terms or in terms of renewable energy consumption share. By opposition, results point that in low to low-middle per capita (GDPPC) countries, the impact of renewable energy consumption in absolute terms is positive, while considering the share of this consumption results point for a positive effect of renewable energy consumption share over per capita income in very low per capita income countries.

Substitution has a huge cost imposed on the energy industry structure imposing high challenges as results seem to point. Policymakers have an extreme dilemma when weighting the costs in the face of the environmental benefits since results appear to indicate that this burden will be made at the cost of lower-income and development. This also implies that nonrenewable energy consumption is more important than renewable energy consumption for economic growth in the OECD countries, and sustainable economic growth cannot be achieved solely through energy consumption from renewable sources and thus minimizing environmental degradation if fossil sources are still a greater contributor of economic growth.

Policymakers should thus reduce first the dependence of income from fossil fuel sources, and only afterward bet in renewable sources by increasing their share in total energy consumption. These economies should devise energy policies to shift from nonrenewable energy to renewable, without harming their economic growth path and bearing in mind the need for environmental improvements. In doing so, they might take up labor, capital, and research and development substitution policies to reduce the higher dependence on fossil energies (whereas they should forgo revenues from exports), which will not be easy without imposing trade deficits in some of these countries. But, continuing this trajectory and noticing the impact the share of renewable energy would impose over economic growth, it becomes urgent the awareness with respect to environmental degradation if they simply continue to follow the present trajectory in terms of energy consumption mix.

Credit author statement

Eyup Dogan: empirical analysis, results, supervision; Buket Altinoz: methodology, results; Mara Madaleno: results and conclusion; Dilvin Taskin: Introduction, review.

Appendix A

Table A.1

Results from panel unit root test (Original study I-L and our estimation are the same).

	Form	Method	Value	p-value	Conclusion
CAP	Trend and intercept	LLC	2.083	0.981	Non-stationary
		Breit t	− 0.889	0.187	Non-stationary
		IPS	− 3.359	0.000	Stationary
		ADF-Fisher	120.834	0.000	Stationary
		PP-Fisher	84.560	0.030	Stationary
	Intercept	LLC	− 2.181	0.015	Stationary
		IPS	1.878	0.970	Non-stationary
		ADF-Fisher	37.578	0.994	Non-stationary
		PP-Fisher	31.523	1.000	Non-stationary
	None	LLC	5.811	1.000	Non-stationary
		ADF-Fisher	10.171	1.000	Non-stationary
		PP-Fisher	12.817	1.000	Non-stationary
EMPL	Trend and intercept	LLC	− 1.059	0.145	Non-stationary
		Breit t	2.897	0.998	Non-stationary

Table A.1 (*continued*)

	Form	Method	Value	p-value	Conclusion
		IPS	− 0.330	0.371	Non-stationary
		ADF-Fisher	90.316	0.011	Stationary
		PP-Fisher	78.317	0.079	Non-stationary
	Intercept	LLC	− 0.883	0.189	Non-stationary
		IPS	1.456	0.927	Non-stationary
		ADF-Fisher	58.716	0.595	Non-stationary
		PP-Fisher	55.019	0.723	Non-stationary
	None	LLC	9.255	1.000	Non-stationary
		ADF-Fisher	10.165	1.000	Non-stationary
		PP-Fisher	9.489	1.000	Non-stationary
RD	Trend and intercept	LLC	− 0.952	0.171	Non-stationary
		Breit t	2.920	0.998	Non-stationary
		IPS	− 0.998	0.159	Non-stationary
		ADF-Fisher	93.981	0.005	Stationary
		PP-Fisher	42.418	0.973	Non-stationary
	Intercept	LLC	− 2.850	0.002	Stationary
		IPS	3.872	1.000	Non-stationary
		ADF-Fisher	37.210	0.995	Non-stationary
		PP-Fisher	64.636	0.385	Non-stationary
	None	LLC	12.139	1.000	Non-stationary
		ADF-Fisher	3.398	1.000	Non-stationary
		PP-Fisher	2.896	1.000	Non-stationary
SRC	Trend and intercept	LLC	3.014	0.999	Non-stationary
		Breit t	4.781	1.000	Non-stationary
		IPS	4.334	1.000	Non-stationary
		ADF-Fisher	50.513	0.851	Non-stationary
		PP-Fisher	42.172	0.975	Non-stationary
	Intercept	LLC	3.461	1.000	Non-stationary
		IPS	3.006	0.999	Non-stationary
		ADF-Fisher	56.722	0.666	Non-stationary
		PP-Fisher	52.678	0.795	Non-stationary
	None	LLC	1.083	0.861	Non-stationary
		ADF-Fisher	49.956	0.864	Non-stationary
		PP-Fisher	46.632	0.927	Non-stationary
TRC	Trend and intercept	LLC	− 6.390	0.000	Stationary
		Breit t	0.816	0.793	Non-stationary
		IPS	− 1.422	0.078	Non-stationary
		ADF-Fisher	92.619	0.007	Stationary
		PP-Fisher	74.828	0.127	Non-stationary
	Intercept	LLC	2.728	0.997	Non-stationary
		IPS	5.309	1.000	Non-stationary
		ADF-Fisher	92.699	0.007	Stationary
		PP-Fisher	24.052	1.000	Non-stationary
	None	LLC	3.714	1.000	Non-stationary
		ADF-Fisher	23.639	1.000	Non-stationary
		PP-Fisher	18.869	1.000	Non-stationary
GDP	Trend and intercept	LLC	6.524	1.000	Non-stationary
		Breit t	4.945	1.000	Non-stationary
		IPS	2.956	0.998	Non-stationary
		ADF-Fisher	52.641	0.796	Non-stationary
		PP-Fisher	50.765	0.845	Non-stationary
	Intercept	LLC	− 6.744	0.000	Stationary
		IPS	0.345	0.635	Non-stationary
		ADF-Fisher	65.366	0.361	Non-stationary
		PP-Fisher	51.783	0.819	Non-stationary
	None	LLC	19.013	1.000	Non-stationary
		ADF-Fisher	2.098	1.000	Non-stationary
		PP-Fisher	0.244	1.000	Non-stationary
GDPPC	Trend and intercept	LLC	− 10.546	0.000	Stationary
		Breit t	5.167	1.000	Non-stationary
		IPS	− 14.669	0.000	Stationary
		ADF-Fisher	287.680	0.000	Stationary
		PP-Fisher	377.407	0.000	Stationary
	Intercept	LLC	− 13.457	0.000	Stationary
		IPS	− 16.121	0.000	Stationary
		ADF-Fisher	354.728	0.000	Stationary
		PP-Fisher	978.683	0.000	Stationary
	None	LLC	− 23.392	0.000	Stationary
		ADF-Fisher	548.352	0.000	Stationary
		PP-Fisher	592.767	0.000	Stationary

Table A.2
Data from 1990 to 2016: GDP as dependent variable.

Quantile		Model I: dGDP				Model II: dGDP			
		dTRC	dCAP	dEMPL	dRD	dSRC	dCAP	dEMPL	dRD
5	Coeff.	0.009	0.042	0.563[a]	0.010	−0.002	0.022	0.514[a]	0.004
	z-stat	1.46	1.46	9.34	0.26	−0.33	0.37	8.55	0.16
10	Coeff.	0.001	0.027	0.440	0.010	−0.002	0.024	0.495[a]	0.025
	z-stat	0.14	0.25	7.35	0.46	−0.28	0.23	6.47	0.77
20	Coeff.	0.011	0.016	0.511[a]	0.028	−0.001	0.008	0.436[a]	0.029
	z-stat	1.45	0.66	5.44	1.33	−0.08	0.12	5.77	1.45
30	Coeff.	0.004	0.024	0.494[a]	0.022	−0.004	0.032	0.489[a]	0.019
	z-stat	0.34	0.40	4.90	1.39	−0.48	0.55	5.31	1.51
40	Coeff.	0.002	0.020	0.462[a]	0.011	−0.008	0.026	0.401[a]	0.027
	z-stat	0.12	0.32	4.79	0.72	−1.15	0.48	4.43	1.55
50	Coeff.	0.006	0.029	0.490a	0.015	−0.008	0.032	0.491[a]	0.015
	z-stat	1.32	1.32	5.19	1.09	−0.72	0.28	3.93	0.78
60	Coeff.	0.003	0.085	0.578[a]	0.025[c]	−0.009	0.040	0.485[a]	0.018
	z-stat	0.42	1.19	3.86	1.77	−0.82	0.53	6.45	1.14
70	Coeff.	0.008	0.052	0.273[b]	0.025	−0.018	0.088	0.530[a]	0.020
	z-stat	0.55	1.39	2.10	1.35	−1.58	1.01	7.29	1.45
80	Coeff.	0.001	0.097	0.512[a]	0.009	−0.015	0.108	0.552[b]	0.020
	z-stat	0.09	0.73	3.50	0.76	−0.50	0.69	2.51	0.74
90	Coeff.	0.011	0.133	0.556[a]	0.016	−0.014	0.119	0.652[a]	0.016
	z-stat	0.42	0.59	4.13	1.38	−1.61	1.12	9.88	0.90
95	Coeff.	0.010	0.256	0.493	0.009	0.013	0.225	0.562[a]	−0.016
	z-stat	0.08	0.47	0.83	0.53	0.36	0.52	3.29	−0.55

Note: [a], [b], [c] denote 1%, 5% and 10% significance level, respectively.

Table A.3
Data from 1990 to 2016: GDPPC as dependent variable.

		Model III: dGDPPC				Model IV: dGDPPC			
Quantile		dTRC	dCAP	dEMPL	dRD	dSRC	dCAP	dEMPL	dRD
5	Coeff.	0.011[b]	0.008	0.414[a]	0.034	−0.005	0.024	0.674[a]	−0.006
	z-stat	2.21	40.24	6.25	1.04	−0.20	0.79	3.76	−0.66
10	Coeff.	0.009	0.001	0.413[a]	0.013	0.003	0.002	0.459[a]	0.004
	z-stat	1.44	0.01	5.78	0.66	0.32	0.06	5.79	0.61
20	Coeff.	0.001	0.021	0.472[a]	0.005	−0.004	0.020	0.434[a]	0.007
	z-stat	0.59	0.34	5.79	0.85	−0.52	0.25	5.12	0.35
30	Coeff.	0.001	0.062	0.613[a]	0.003	−0.004	0.023	0.460	0.015
	z-stat	0.16	0.83	5.13	0.47	−0.56	1.21	5.17	0.74
40	Coeff.	−0.001	0.024	0.44[a]	0.020	−0.008	0.023	0.437[a]	0.021
	z-stat	−0.99	0.91	3.56	0.78	−1.15	2.81	4.14	1.22
50	Coeff.	−0.003	0.079[b]	0.538[a]	0.027[c]	−0.008	0.068[c]	0.533[a]	0.023
	z-stat	−0.23	2.04	4.56	1.59	−1.13	1.86	4.10	1.13
60	Coeff.	−0.004	0.081	0.502[a]	0.022[c]	−0.011[c]	0.071	0.492[a]	0.014
	z-stat	−0.30	1.39	4.06	1.83	−1.73	1.58	6.55	1.31
70	Coeff.	−0.003	0.094	0.468[a]	0.029[c]	−0.014[c]	0.095	0.573[a]	0.022
	z-stat	−0.34	0.96	4.89	1.69	−1.83	0.86	4.65	1.09
80	Coeff.	−0.010	0.118	0.453[a]	0.043[a]	−0.019	0.131	0.569[a]	0.032[c]
	z-stat	−1.14	1.24	3.98	2.57	−0.84	0.55	4.14	1.69
90	Coeff.	−0.016[c]	0.067	0.463[b]	0.029[a]	−0.013	0.131	0.583[a]	0.026[a]
	z-stat	−1.65	0.52	2.01	2.59	−1.36	1.07	4.62	4.06
95	Coeff.	0.028	0.114	0.471[a]	0.016	0.025	0.115	0.704[a]	0.003
	z-stat	0.94	0.74	4.35	0.63	0.43	0.43	6.76	0.16

Note: [a], [b], [c] denote 1%, 5% and 10% significance level, respectively.

References

OECD, IEA, 2011. Green Growth Studies: Energy. https://www.oecd.org/greengrowth/greening-energy/49157219.pdf.

Albulescu, C.T., Tiwari, A.K., Yoon, S.-M., Kang, S.H., 2019. FDI, income, and environmental pollution in Latin America: replication and extension using panel quantiles regression analysis. Energy Econ. 84, 104504. https://doi.org/10.1016/j.eneco.2019.104504.

Al-Mulali, U., Sab, C.N., 2012. The impact of energy consumption and CO2 emission on the economic growth and financial development in the sub Saharan African countries. Energy 39 (1), 180–186.

Álvarez-Herránz, A., Balsalobre, D., Cantos, J.M., Shahbaz, M., 2017. Energy innovations-GHG emissions nexus: fresh empirical evidence from OECD countries. Energy Policy 101, 90–100.

Apergis, N., Danuletiu, D., 2014. Renewable energy and economic growth: evidence from the sign of panel long-run causality. International Journal of Energy Economics and Policy 4 (4), 578–587.

Apergis, N., Payne, J.E., 2010. Energy consumption and growth in South America: evidence from a panel error correction model. Energy Econ. 32 (6), 1421–1426.

Apergis, N., Payne, J.E., 2011. The renewable energy consumption-growth nexus in Central America. Appl. Energy 88 (1), 343–347.

Apergis, N., Payne, J.E., 2012. Renewable and non-renewable energy consumption-growth nexus: evidence from a panel error correction model. Energy Econ. 34 (3), 733–738. https://doi.org/10.1016/j.eneco.2011.04.007.

Apergis, N., Tang, C.F., 2013. Is the energy-led growth hypothesis valid? New evidence from a sample of 85 countries. Energy Econ. 38, 24–31. https://doi.org/10.1016/j.eneco.2013.02.007.

Arifin, J., Syahruddin, N., 2011. Causality relationship between renewable and non-renewable energy consumption and GDP in Indonesia. Economics and Finance in Indonesia 59 (1), 1–18.

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., Farhani, S., 2018. How economic growth, renewable electricity and natural resources contribute to CO_2 emissions? Energy Policy 113, 356–367. https://doi.org/10.1016/j.enpol.2017.10.050.

Bhattacharya, M., Paramati, S.R., Ozturk, I., Bhattacharya, S., 2016. The effect of renewable energy consumption on economic growth: evidence from top 38 countries. Appl. Energy 162, 733–741. https://doi.org/10.1016/j.apenergy.2015.10.104.

Bitler, M.P., Gelbach, J.B., Hoynes, H.W., 2006. What mean impacts miss: distributional effects of welfare reform experiments. Am. Econ. Rev. 96, 988–1012.

Bourcet, C., 2020. Empirical determinants of renewable energy deployment: a systematic literature review. Energy Econ. 85, 104563.

Bowden, N., Payne, N., 2009. The causal relationship between US energy consumption and real output: a disaggregated analysis. J. Policy Model 31 (2), 180–188.

Canay, I.A., 2011. A simple approach to quantile regression for panel data. Econometrics Journal 14, 368–386. https://doi.org/10.1111/j.1368-423X.2011.00349.x.

Chang, T., Gupta, R., Inglesi-Lots, R., Simo-Kengne, B., Smithers, D., Trembling, A., 2015. Renewable energy and growth: evidence from heterogeneous panel of G7 countries using granger causality. Renew. Sust. Energ. Rev. 52, 1405–1412. https://doi.org/10.1016/j.rser.2015.08.022.

Chen, W., Lei, Y., 2018. The impacts of renewable energy and technological innovation on environment-energy-growth nexus: new evidence from a panel quantile regression. Renew. Energy 123, 1–14. https://doi.org/10.1016/j.renene.2018.02.026.

Chen, C., Pınar, M., Stengos, T., 2020. Renewable energy consumption and economic growth nexus: evidence from a threshold model. Energy Policy 139, 111295.

Chontanawat, J., Hunt, L.C., Pierse, R., 2008. Does energy consumption cause economic growth?: evidence from a systematic study of over 100 countries. J. Policy Model 30 (2), 209–220. https://doi.org/10.1016/j.jpolmod.2006.10.003.

Destek, M.A., Sinha, A., 2020. Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: evidence from organisation for economic co-operation and development countries. J. Clean. Prod. 242, 1–11.

Dogan, E., Ozturk, I., 2017. The influence of renewable and non-renewable energy consumption and real income on CO2 emissions in the USA: evidence from structural break tests. Environ. Sci. Pollut. Res. 24, 10846–10854.

Frees, E.W., 1995. Assessing cross-sectional correlation in panel data. J. Econ. 69, 303–414.

Friedman, M., 1937. The use of ranks to avoid the assumption of normality implicit in the analysis in variance. J. Am. Stat. Assoc. 32, 675–701.

Gnansounou, E., 2008. Assessing the energy vulnerability: case of industrialised countries. Energy Policy 36 (10), 3734–3744. https://doi.org/10.1016/j.enpol.2008.07.004.

Harding, M., Lamarche, C., 2009. A quantile regression approach for estimating panel data models using instrumental variables. Econ. Lett. 104 (3), 133–135. https://doi.org/10.1016/j.econlet.2009.04.025.

Hedenus, F., Azar, C., Johansson, D.J., 2010. Energy security policies in EU-25-The expected cost of oil supply disruptions. Energy Policy 38 (3), 1241–1250. https://doi.org/10.1016/j.enpol.2009.01.030.

IEA, 2015. World Energy Outlook 2015. IEA, Paris https://www.iea.org/reports/world-energy-outlook-2015.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econ. 115 (1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7.

Inglesi-Lotz, R., 2016. The impact of renewable energy consumption to economic growth: a panel data application. Energy Econ. 53, 58–63. https://doi.org/10.1016/j.eneco.2015.01.003.

Kato, K., Galvao, A.F., Montes-Rojas, G.V., 2012. Asymptotics for panel quantile regression models with individual effects. J. Econ. 170 (1), 76–91. https://doi.org/10.1016/j.jeconom.2012.02.007.

Khan, S.A.R., Zhang, Y., Kumar, A., Zavadskas, E., Streimikiene, D., 2020. Measuring the impact of renewable energy, public health expenditure, logistics, and environmental performance on sustainable economic growth. Sustain. Dev. 1–11.

Koenker, R., 2004. Quantile regression for longitudinal data. J. Multivar. Anal. 91 (1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006.

Lamarche, C., 2010. Robust penalized quantile regression estimation for panel data. J. Econ. 157 (2), 396–408. https://doi.org/10.1016/j.jeconom.2010.03.042.

Lee, C.C., Chang, C.P., 2008. Energy consumption and economic growth in Asian economies: a more comprehensive analysis using panel data. Resour. Energy Econ. 30 (1), 50–65. https://doi.org/10.1016/j.reseneeco.2007.03.003.

Menegaki, A., 2011. Growth and renewable energy in Europe: a random effect model with evidence for neutrality hypothesis. Energy Econ. 33 (2), 257–263. https://doi.org/10.1016/j.eneco.2010.10.004.

Menyah, K., Wolde-Rufael, Y., 2010. Energy consumption, pollutant emissions and economic growth in South Africa. Energy Econ. 32 (6), 1374–1382. https://doi.org/10.1016/j.eneco.2010.08.002.

Ocal, O., Aslan, A., 2013. Renewable energy consumption–economic growth nexus in Turkey. Renew. Sust. Energ. Rev. 28, 494–499. https://doi.org/10.1016/j.rser.2013.08.036.

Odhiambo, N.M., 2010. Energy consumption, prices and economic growth in three SSA countries: a comparative study. Energy Policy 38 (5), 2463–2469. https://doi.org/10.1016/j.enpol.2009.12.040.

OECD, 2011. Towards green growth. OECD Publishing.

Ozcan, B., Ozturk, I., 2019. Renewable energy consumption-economic growth nexus in emerging countries: a bootstrap panel causality test. Renew. Sust. Energ. Rev. 104, 30–37. https://doi.org/10.1016/j.rser.2019.01.020.

Pan, G., Gao, J., Yang, Y., Guo, M.H., 2015. Cross-Sectional Independence Test for a Class of Parametric Panel Data Models. Monash University, Department of Econometrics and Business Statistics https://doi.org/10.2139/ssrn.2665105 ISSN: 1440-771X.

Pao, H.-T., Tsai, C.-M., 2010. CO2 emissions, energy consumption and economic growth in BRIC countries. Energy Policy 38 (12), 7850–7860. https://doi.org/10.1016/j.enpol.2010.08.045.

Pao, H.-T., Li, Y.-Y., Fu, H.-C., 2014. Clean energy, non-clean energy, and economic growth in the MIST countries. Energy Policy 67, 932–942. https://doi.org/10.1016/j.enpol.2013.12.039.

Payne, J.E., 2009. On the dynamics of energy consumption and output in the US. Appl. Energy 86 (4), 575–577.

Payne, J., 2011. On biomass energy consumption and real output in the US. *Energy Sources Part B* 6 (1), 47–52.

Pedroni, P., 1999. Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxf. Bull. Econ. Stat. 61, 653–670.

Pedroni, P., 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis: new results. Econometric Theory 20 (3), 597–625.

Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels. Available at:. http://ftp.iza.org/dp1240.pdf.

Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ. 22, 265–312.

Pesaran, M.H., Yamagata, T., 2008. Testing slope homogeneity in large panels. J. Econ. 142 (1), 50–93.

Powell, D., 2016. Quantile Regression with Nonadditive Fixed Effects. Web address. https://works.bepress.com/david_powell/1/.

Sadorsky, P., 2009a. Renewable energy consumption, CO_2 emissions and oil prices in the G7 countries. Energy Econ. 31 (3), 456–462. https://doi.org/10.1016/j.eneco.2008.12.010.

Sadorsky, P., 2009b. Renewable energy consumption and income in emerging economies. Energy Policy 37 (10), 4021–4028. https://doi.org/10.1016/j.enpol.2009.05.003.

Sarafidis, V., Wansbeek, T., 2012. Cross-sectional dependence in panel data analysis. Econ. Rev. 31 (5), 483–531.

Sarkodie, S.A., Strezov, V., 2019. Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. Sci. Total Environ. 646, 862–871. https://doi.org/10.1016/j.scitotenv.2018.07.365.

Shahbaz, M., Khan, S., Tahir, M.I., 2013. The dynamic links between energy consumption, economic growth, financial development and trade in China: fresh evidence from multivariate framework analysis. Energy Econ. 40, 8–21. https://doi.org/10.1016/j.eneco.2013.06.006.

Shahbaz, M., Loganathan, N., Zeshan, M., Zaman, K., 2015. Does renewable energy consumption add in economic growth? An application of auto-regressive distributed lag model in Pakistan. Renew. Sust. Energ. Rev. 44, 576–585.

Shahbaz, M., Rasool, G., Ahmed, K., Mahalik, M.K., 2016. Considering the effect of biomass energy consumption on economic growth: fresh evidence from BRICS region. Renew. Sust. Energ. Rev. 60, 1442–1450.

Sharif, A., Mishra, S., Sinha, A., Jiao, Z., Shahbaz, M., Afshan, S., 2020. The renewable energy consumption-environmental degradation nexus in top-10 polluted countries: fresh insights from quantile-on-quantile regression approach. Renew. Energy 150, 670–690.

Sim, N., Zhou, H., 2015. Oil prices, US stock return, and the dependence between their quantiles. J. Bank. Financ. 55, 1–8.

Sinha, A., Shahbaz, M., Sengupta, T., 2018. Renewable energy policies and contradictions in causality: a case of next 11 countries. J. Clean. Prod. 197 (1), 73–84.

Stern, N., 2007. Stern Review on the Economics of Climate Change. Retrieved from. https://webarchive.nationalarchives.gov.uk/20100407172811/http://www.hm-treasury.gov.uk/stern_review_report.htm.

Tang, C.F., Tan, B.W., Ozturk, I., 2016a. Energy consumption and economic growth in Vietnam. Renew. Sust. Energ. Rev. 54, 1506–1514.

Tang, C.F., Tiwari, A.K., Shahbaz, M., 2016b. Dynamic inter-relationships among tourism, economic growth and energy consumption in India. Geosystem engineering 19 (4), 158–169.

Tiwari, A.K., 2011. A structural VAR analysis of renewable energy consumption, real GDP and CO2 emissions: evidence from India. Econ. Bull. 31 (2), 1793–1806.

Troster, V., Shahbaz, M., Uddin, G.S., 2018. Renewable energy, oil prices, and economic activity: a granger-causality in quantiles analysis. Energy Econ. 70, 440–452. https://doi.org/10.1016/j.eneco.2018.01.029.

Wadström, C., Wittberg, E., Uddin, G.S., Jayasekera, R., 2019. Role of renewable energy on industrial output in Canada. Energy Econ. 81, 626–638. https://doi.org/10.1016/j.eneco.2019.04.028.

Westerlund, J., 2007. Testing for error correction in panel data. Oxf. Bull. Econ. Stat. 69 (6), 709–748.

Yildirim, E., Sarac, S., Aslan, A., 2012. Energy consumption and economic growth in the USA: evidence from renewable energy. Renew. Sust. Energ. Rev. 16 (9), 6770–6774. https://doi.org/10.1016/j.rser.2012.09.004.