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# Energy production-income-carbon emissions nexus in the perspective of N.A.F.T.A. and B.R.I.C. nations: a dynamic panel data approach

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## ABSTRACT

This paper has attempted to examine the impact of innovation and energy production (i. e., oil, natural gas, and coal) on carbon dioxide emissions (CO<sub>2</sub>e) in the context of the Environmental Kuznets Curve (E.K.C.) hypothesis. Data were analysed for economies in B.R.I.C. (Brazil, India, Russia, and China) and North American Free Trade Agreement (N.A.F.T.A.) (the U.S., Canada, and Mexico) from 1992 to 2016. Based on the Hausman specification test, the panel mean group (P.M.G.) estimation approach was adopted. The empirical results suggested that an upsurge in coal and oil production has increased, while the gas production has disrupted CO<sub>2</sub>e in the long run. An insignificant yet positive relationship was observed between innovation and CO<sub>2</sub>e. The positive effect of per capita income and the negative effect of per capita income (square) on CO<sub>2</sub>e validated the presence of the E.K.C. hypothesis in the sampled economies. With the results showing an acute over-dependency on carbon-intensive energy sources (coal and oil), an imminent need exists for production of natural gas; at the same time, more investments are needed for exploration of low carbon-intensive renewable energy sources for environmental sustainability.

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## 1. Introduction

Even though energy is considered as one of the most fundamental units of production for economic development (Alam et al., 2016; Danish, Zhang, & Wang, 2017), several environmentalists and economists claim that energy consumption causes environmental degradation (Ahmad et al., 2018; Chandia, et al., 2018; Rahman,

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Hongbo, and Ahmad, 2019). From the plethora of studies conducted over the past decades, scholars have found a robust relationship between climate change and CO<sub>2</sub>e, mainly originating from the consumption (cf. Chen et al., 2016; Dogan & Aslan, 2017; Mohiuddin et al., 2016; Rahman & Ahmad, 2019). Prior studies have shown that the consumption and production of energy experience an increase in the early phases of economic development as economies strive to fulfill the energy requirements of various sectors for production of goods/products, transportation, and beyond. In theoretical terms, the E.K.C. hypothesis explains the nexus between pollution, economic growth and income. It posits that pollution follows the rising curve of economic growth, reaches a certain level, and then declines with the improving levels of income (cf. Ahmad et al. 2018; Danish, Zhang, & Wang, 2017; Rahman & Ahmad, 2019). Tamazian, Chousa, and Vadlamannati (2009) confirm that developed and developing economies – the U.S. (23%), the OECD nations (24%), Japan (5.27%), China (11%), Russian Federation (3.80%), India (3%), and Brazil (0.94%) – were among the top global economies in the 1990 vis-à-vis CO<sub>2</sub>e from energy production. As the aftermaths of the Industrial Revolution that occurred nearly two centuries ago, the world has witnessed a phenomenal rise in global population, technological advancement, and material well-being, often at the cost of the global environment (Azevedo, Sartori, & Campos, 2018). Despite the potential implications of energy production for the global CO<sub>2</sub>e, current literature remains deficient in empirical studies that examine the impact of energy production on the environment, conjointly in the Brazil, India, Russia and China (B.R.I.C.) and North American Free Trade Agreement (N.A.F.T.A.) economies.

In response to the stated knowledge gap, this study has attempted to investigate the environmental implications of countries with leading economies (G.D.P.), population, and O<sub>2</sub>e. With the G.D.P. of these economies predicted to surpass G7 nations by 2050, the sampled economies are often proposed to shape the future of global sustainability (Azevedo et al., 2018). That said, an alarming increase in the levels of CO<sub>2</sub>e in Brazil (1.15%), Russia (6%), India (5%), and China (16%) in 2007 has raised serious doubts whether [or not] these emerging economies can shoulder the responsibility of leading the world into a sustainable future. China, for instance, ranks among the topmost energy consuming and producing nations of the world. As per the British Petroleum Report (2017), coal production and consumption (leading sources of CO<sub>2</sub>e) accounted for approximately 62% of the total energy mix in China. In the same year, the reported estimates showed that CO<sub>2</sub>e from energy consumption augmented by 1.6%, natural gas production increased by 8.5%, and coal production increased by 3.6%. Globally, the coal production peaked by 3.2% or 105 million tones oil equivalent (Mtoe), representing an all-time high growth rate ever since 2011. The British Petroleum Report (2019), however, indicated an aggregate increase of only 1% in the global production of coal. Despite the three successive phases of decline in coal production from 2014 to 2016, the levels of coal production in China and India have increased by 4 (Mtoe) and 18 (Mtoe), respectively. Russia, on the other hand, achieved an all-time high growth rate of 8.2% in natural gas production by providing 17.3% of the global output. The country ranked among the topmost oil and gas exporters, trailing only behind the U.S. Due to the

increasing demand for coal (3%) in the power generation sector, coal consumption experienced an increase of around 4%, contributing to a significant increase in CO<sub>2</sub>e (1.3%). The total energy consumption mix comprised of natural gas (52.3%), oil (21.9%), and coal (13.2%). While the energy production accounted for almost 10.4% of the global output in 2017, the country's share in the global production of gas (17.3%), oil (12.6%), and coal (5.5%) were equally significant. Keeping in view the scope of economic activities in the countries discussed above, it becomes a research imperative to explore the effects of energy production on CO<sub>2</sub>e in the context of the E.K.C.

Many academics argue that heavy reliance on fossil fuels (i.e., oil, natural gas, and coal) for economic growth have led to CO<sub>2</sub>e and global warming, and thus, an imminent need exists to focus on the harmful impact of fossil fuel-based energy consumption and production on climate change and pollution (e.g., Danish, Wang, & Wang, 2017; Salim & Ra, 2012). The methodological novelty of this work resides in several aspects. First, the article quantifies the association between CO<sub>2</sub>e and energy production from natural gas, coal, and oil in the context of B.R.I.C.S. and N.A.F.T.A. thereby offering the much-needed empirical insight on the topmost energy consuming and producing economies in the world. Second, although few scholars have attempted to explain the nexus between energy production and CO<sub>2</sub>e, most prior estimates are based on a single non-renewable energy source (e.g., oil or coal). Third, most previous studies have examined energy consumption at an aggregated level using time-series or panel data, while underestimating the influence of cross-sectional dependence (C.D.). To address this methodological issue, The present study, has adopted the pooled mean group technique for the panel data to verify the cointegration among variables. Finally, this work extends prior theory and research in the E.K.C. paradigm by integrating energy production and innovation into the equation.

## 2. Literature review

The nexus between CO<sub>2</sub>e and energy consumption has attracted significant academic interest in the past few decades, where academics have used different econometrics techniques, samples, and periods to explain the energy consumption-CO<sub>2</sub>e nexus. Past empirical evidence that supports a positive interaction between energy consumption and CO<sub>2</sub>e includes studies conducted for many countries and regions: China (Ahmad et al., 2018; Zhang & Cheng, 2009); a panel of 69 countries based on income group (Sharma, 2011); Turkey (Ozturk & Acaravci, 2013); Indonesia (Shahbaz et al., 2013); Tunisia (Farhani, Chaibi, & Rault, 2014); 17 African economies (Boutabba, 2014); a panel of European Union nations (Dogan & Aslan, 2017; Kasman & Selman Duman, 2015); the U.S. (Dogan & Turkekul, 2015); 12 sub-Saharan African nations (Esso & Keho, 2016); the Association of Southeast Asian Nations (Baek, 2016; Wang, Chen, & Kubota, 2016; Zhu et al., 2016); four emerging economies (Alam et al., 2016); Bulgaria and Greece (Obradović & Lojanica, 2017); Japan (Shahbaz, Shahzad, & Mahalik, 2017); Pakistan (Mirza & Kanwal, 2017; Rahman & Ahmad, 2019); a panel of various countries based on income group (Wang, Li, & Fang, 2017); 25

African nations (Zoundi, 2017a); and Ghana (Appiah, 2018). Beyond that, few researchers have also studied the association between CO<sub>2</sub> and energy use at a disaggregated level. For instance, Alkhatlan (2013) investigated the link between growth, pollution, and energy consumption at both aggregated and disaggregated level for Saudi Arabia. Using the total energy consumption for the aggregated level of analysis and fossil-fuels (oil, gas, and electricity) for the disaggregated level, the authors found a negative impact of gas and electricity consumption on CO<sub>2</sub>e. Alternatively, Ahmad et al. (2016) examined the short and long-term connection between CO<sub>2</sub>e and energy use at the disaggregated and aggregated level in India for the time period 1971–2014 using the A.R.D.L. model. The empirical model suggested that the consumption of aggregated and disaggregated energy (including oil, coal, gas, and electricity) have different impacts on CO<sub>2</sub>e.

Considering energy production, past research on the energy production-CO<sub>2</sub>e-income nexus remains limited to this date. Ghosh (2010), for instance, tested the same relationship in India for the period 1971–2006 and validated a one-way causality run from growth to energy supply and from energy supply to CO<sub>2</sub>e in the short-term. Mohiuddin et al. (2016) examined the relationship between energy use, GDP, CO<sub>2</sub>e, and electricity production (natural gas, oil, and coal) in Pakistan for the period 1971–2013. Using Vector-error Correction Model (V.C.E.M.), the authors found that a 1% increase in oil-based energy production causes a 13.7% increase in CO<sub>2</sub>e, energy consumption, gas-based energy production, and G.D.P. were identified as the key determinants of CO<sub>2</sub>e. In another study, Danish et al. (2017) examined the association between economic growth, CO<sub>2</sub>e, and energy production in Pakistan for the period 1970–2011. The empirical estimates suggested that energy production from fossil fuel is a strong determinant of CO<sub>2</sub>e, and that, a two-way causality exists between CO<sub>2</sub>e and energy production in the long run. Moreover, extant works that examine income and income square in the context of the E.K.C. hypothesis have provided sufficient evidence that supports that a rise in income leads to environmental degradations during the early stages of economic growth, but after reaching a certain level the pollution diminishes with increasing levels of income (cf. Danish, Zhang, & Wang, 2017; Esso & Keho, 2016; Jalil & Mahmud, 2009; Kiviyiro & Arminen, 2014; Ozturk & Acaravci, 2013; Pao & Tsai, 2011; Rahman & Ahmad, 2019; Saboori, Sulaiman, & Mohd, 2012; Sinha & Shahbaz, 2018). In the same context, some researchers have also assessed the effects of research and development (R&D) on CO<sub>2</sub>e. For instance, Khan, Sisi, and Siqun (2018) found that research and development (R&D) mitigates CO<sub>2</sub>e through various innovation activities and adaptations of new green technologies. Using a non-parametric approach for G7 nations, Churchill, Inekwe, and Smyth (2019) observed that the association between R&D and CO<sub>2</sub>e was time-dependent, where the coefficient was found to be negative for three quarters and positive for a 35-year period. Mensah et al. (2018) also confirmed that innovation led to CO<sub>2</sub>e in most of the 28 OECD sampled economies, though such negative effects varied across countries. Retrospectively, it appears that most prior studies have predominantly focused on the relation between CO<sub>2</sub>e and energy consumption rather than energy production, a knowledge gap that has yet to be addressed.

### 3. Research methodology

#### 3.1. Model specifications

The current model was developed in line with the previous research on the E.K.C. hypothesis (cf. Ahmad et al., 2018; Danish et al., 2017; Rahman & Ahmad, 2019). Following the Pesaran, Pesaran, Shin, and Smith (1999) assertions, the short and long-term effects were assessed using the P.M.G. techniques that permit estimation of short-term causality test. This technique is used to measure the robustness of the coefficients correlated to the lagged difference and the long-term causality associated with the E.C.T. coefficient. Besides, this method facilitates the assessment of cross-country heterogeneity by allowing for short-run adjustment and the speed of convergence across countries (Park, 2018), yet in effect, the short-term coefficients are not restricted to be the same across countries (Fromentin, 2017). Based on such assertions, the following model was specified for analysis in the current study.

$$CO2_{it} = f (CP, OP, GP, Y, Y^2, PT) \tag{1}$$

The log-linear form of eq. (1) can be rewritten as follow:

$$LCO2_{it} = \beta_0 + \beta_1 LCP_{it} + \beta_2 LOP_{it} + \beta_3 LGP_{it} + \beta_4 Y_{it} + \beta_5 Y^2_{it} + \beta_6 PT_{it} + E_{it} \tag{2}$$

Where:  $i = 1 \dots 7$  (proxy for countries);  $t =$  time period;  $CO2 =$  carbon dioxide emissions or  $CO2e$ ;  $CP =$  coal production;  $OP =$  oil production;  $GP =$  gas production;  $Y =$  per capita income;  $Y^2 =$  per capita income (squared);  $PT =$  total patent applications (proxy for innovations);  $L =$  log form;  $\mathcal{E} =$  error terms;  $\beta_0 =$  constant;  $(\beta_1 - \beta_6) =$  coefficients of each independent variables. By re-formulating eq. (2), we obtained attained eq. (3) depicting the Pesaran et al. (1999) P.M.G. techniques for detecting the speed of short-term adjustment with long-term effects estimation.

$$LCO2_{it} = \sum_{j=1}^p \gamma_{ij} LCO2_{i,t-j} + \sum_{j=0}^p \sigma_{ij} X_{i,t-j} + \mu_i + \mathcal{E}_{it} \tag{3}$$

Where:  $X_{it}$  is  $[6 \times 1] =$  vectors of explanatory variables i.e.,  $X_{it} = (CP, OP, GP, Y, Y^2, PT)$ ;  $\mu_i =$  fixed effect;  $\mathcal{E}_{it} =$  independently distributed term across  $i$  and  $t$  with variances  $\delta_i^2 > 0$ ;  $0 =$  dispersed separately of the regressors; and  $X_{i,t} =$  error correction models to short-run dynamics, as shown below in eq. (4):

$$\begin{aligned} \Delta LCO2_{it} = & \beta_0 + \sum_{i=1}^p \gamma_i \Delta LCO2_{t-i} + \sum_{j=1}^q \sigma_j \Delta LCP_{t-j} + \sum_{m=1}^q \partial_m \Delta LOP_{t-m} \\ & + \sum_{r=1}^q \emptyset_r \Delta LGP_{t-r} + \sum_{s=1}^q \theta_s \Delta LY_{t-s} + \sum_{V=1}^q \omega_V \Delta LY^2_{t-V} + \sum_{w=1}^q \zeta_w \Delta LPT_{t-w} \\ & + \vartheta ECT_{t-1} + \mathcal{E}_{it} \end{aligned} \tag{4}$$

The short-term effects of each explanatory variable were attained with the differences term ( $\Sigma$ ) through lag length 'q,' as per the Akaike Information Criterion (A.I.C.) and A.R.D.L. (1, 1, 1, 1, 1).

### **3.2. Data sources and variables**

The data were collected from the British Petroleum Statistic Reports (BP, 2017) and the World Bank Indicators (WDI, 2018) for the period 1992–2016. The balance data comprised of some socio-economic indicators of emerging economies in B.R.I.C. and N.A.F.T.A. The selection of study sample was based on the rationale that the selected countries shared socio-economic characteristics: CO<sub>2</sub>e, economic activities, population growth, and energy production. The availability of complete and balanced data, especially for the Russian Federation, was another reason for sample selection. For data sources and variable measurements, please see the details in Appendix A. The econometric analyses were conducted using the S.T.A.T.A. 13 software.

For this study, CO<sub>2</sub>e (measured in Mtoe) was taken as a dependent variable (a proxy for environmental quality), while other dependent variables comprised of coal, natural gas production (measured in Mtoe), and oil (measured in Mt). Following Mensah et al. (2018), we used the patent application (a proxy for innovation) as a control variable consistent. Instead of using R&D data, the availability of patent data in the balance form was a primary reason for data selection. The availability of this data as a public document with complete information offers considerable credence on the background and activities of assignees, while it simultaneously originates from a novel process that combines R&D activities and productivity (Hasan & Tucci, 2010). For the dependent variables, we used per capita real income and its square (at constant 2010 U.S.D.) and transformed constant G.D.P. by dividing it with the total population.

### **3.3. Data analysis**

As per the generally accepted procedure, the C.D. between the chosen variables across the panel data was scrutinised using the Pesaran (2004) C.D. test. Despite the balanced data, the C.D. test was considered critical to avoid the risk of model spuriousness and biased results. The panel unit-root tests are often considered as a methodological requirement before examining co-integration between variables. Panel unit-tests are often recommended as a prerequisite before examining the co-integration between variables. Thus, the Levin, Lin, and Chu (2002) (L.L.C.) panel unit-root test, an extension of the Augmented Dickey-Fuller (A.D.F.) test, was conducted at the level and first difference. Zoundi (2017b), however, points out a methodical limitation in the L.L.C. tests, i.e., the autoregressive coefficient is assumed to be constant across the panels that are expected to suffer from power loss. Breitung (2000) offers a remedial measure to deal with such a problem by proposing a test that addresses potential bias generated due to the L.L.C. test. As the presence of I(1) in the panel (as in present case) prompts exploring the long-run estimates (Ahmad et al., 2018; Kahia, Safouane Ben Aissa, & Lanouar, 2017), Kao (1999) test of co-integration was

adopted to test the null hypothesis (no co-integration) vs the alternative hypothesis (co-integration). As a conceptual development, Kao (1999) utilised both A.D.F. and D.F. to test cointegration in the panel, an approach considered equal to the Engel-Granger techniques (Zaman, Khan, & Rusdi, 2016).

#### 4. Results and discussion

Table 1 displays the descriptive statistics of all variables. As seen below, innovation (patents) demonstrated substantial variance than other variables in the N.A.F.T.A. economies, possibly due to the higher standard deviation. In terms of country-wise statistics, gas production and real per capita income were found to be more volatile than other variables in Brazil and Russia, respectively. With higher standard deviation values, innovation displayed higher volatility than real per capita income, coal, oil, and gas production in India and China. With a probability value of less than 5%, CO<sub>2</sub>e and coal production reflected an abnormal distribution for Russia and the U.S., respectively.

Table 2 shows the results of the C.D. test. The empirical outputs provided sufficient evidence for the rejection of the null hypothesis of no-C.D. at a 1% level, while simultaneously confirming the alternative hypothesis of C.D. between considered variables. For the test of stationarity, Table 3 exhibits that all the data are non-stationary at the level and becomes stationary at first difference. After performing the L.L.C. and Breitung unit-root test, the estimates reflected the existence of I (1) integration for all variables; subsequently, allowing for testing the hypothesis of cointegration between considered variables. Table 4 displays the results of the residual co-integration test, which strongly rejected the null hypothesis (at 1% critical value) and offered sufficient evidence of cointegration among the variables.

Table 5 presents the results of long-term parameter estimators, namely, the dynamic fixed effect (D.F.E.), mean group (M.G.), and pooled means group. After calculating the pooled mean group estimates for the model, we proceeded with the D.F.E. and M.G. The pooled mean group estimator follows the assumption that long-term elasticities are same across all panel countries and the panels, to some extent, will share some common characteristics in the long run. Instead, the M.G. estimator is considered less informative given that all cases in the panel are assumed to be unique with no similarities. Using the Hausman (1978) specification test, the null hypothesis of homogeneity was based on two distinct comparisons: (a) M.G.-pooled means group (b) D.F.E.-pooled means group. This specification test supported the pooled means group; against M.G. and D.F.E. as the *p* values were found to be higher than 0.5 in both cases.

Table 5 shows that coefficients of all variables are positive and statistically significant, except for innovation. As predicted, the empirical results reflected the high dependency of sampled economies on coal and oil energies, where a 1% increase in the production of coal and oil increased CO<sub>2</sub>e by 0.37% and 0.06%, respectively. Consistent with the British Petroleum Report (2017), current findings offered empirical evidence that oil and coal production are among the primary determinants of CO<sub>2</sub>e. Moreover, the results showed that a 1% rise in natural gas production reduced



**Table 1.** Descriptive statistics.

| Variables   | Statistic   | N.A.F.T.A. |         |         | B.R.I.C. |         |         |         |
|-------------|-------------|------------|---------|---------|----------|---------|---------|---------|
|             |             | The US     | Canada  | Mexico  | Brazil   | Russia  | India   | China   |
| CO2         | Mean        | 3.7553     | 2.7219  | 2.5964  | 2.5246   | 3.1946  | 3.0785  | 3.7098  |
|             | Median      | 3.7569     | 2.7325  | 2.6111  | 2.5107   | 3.1823  | 3.0495  | 3.7261  |
|             | Maximum     | 3.7876     | 2.7568  | 2.6918  | 2.7061   | 3.3215  | 3.5662  | 3.9649  |
|             | Minimum     | 3.7161     | 2.6519  | 2.4505  | 2.3360   | 3.3165  | 2.8290  | 3.4121  |
|             | Std. Dev.   | 0.0208     | 0.0306  | 0.0807  | 0.1054   | 0.0372  | 0.1658  | 0.2064  |
|             | Skewness    | -0.2825    | -1.0156 | -0.4568 | 0.1143   | 2.2324  | 0.1796  | -0.0145 |
|             | Kurtosis    | 1.8459     | 3.0056  | 1.8144  | 2.1768   | 7.4703  | 1.7557  | 1.3096  |
|             | Jarque-Bera | 1.4157     | 4.2977  | 2.3336  | 0.7603   | 41.582  | 1.7470  | 2.9770  |
|             | Probability | 0.4926     | 0.1166  | 0.3113  | 0.6837   | 0.0000  | 0.4174  | 0.5227  |
|             | Y           | Mean       | 4.6569  | 4.6465  | 3.9353   | 3.9838  | 3.9229  | 2.9827  |
| Median      | 4.6777      | 4.6643     | 3.9375  | 3.9689  | 3.9224   | 2.9556  | 3.3931  |         |
| Maximum     | 4.7130      | 4.7009     | 3.9831  | 4.0759  | 4.0742   | 3.2598  | 3.833   |         |
| Minimum     | 4.5630      | 4.5454     | 3.8637  | 3.8919  | 3.7408   | 2.7394  | 2.9488  |         |
| Std. Dev.   | 0.0477      | 0.0507     | 0.0356  | 0.0585  | 0.1206   | 0.1660  | 0.2775  |         |
| Skewness    | -0.6962     | -0.6983    | -0.3895 | 0.2525  | -0.1204  | 0.2064  | 0.0040  |         |
| Kurtosis    | 2.2003      | 2.0647     | 2.1078  | 1.6477  | 1.4463   | 1.7556  | 1.7166  |         |
| Jarque-Bera | 2.6861      | 2.9432     | 1.4612  | 2.1703  | 2.5775   | 1.7904  | 1.7155  |         |
| Probability | 0.2610      | 0.2295     | 0.4812  | 0.3378  | 0.5925   | 0.4085  | 0.4241  |         |
| CP          | Mean        | 2.7337     | 1.5679  | 0.7269  | 0.4122   | 2.1519  | 2.2682  | 3.0262  |
|             | Median      | 2.7459     | 1.5519  | 0.7335  | 0.3906   | 2.1491  | 2.2591  | 3.0441  |
|             | Maximum     | 2.7804     | 1.6564  | 0.9717  | 0.5693   | 2.2850  | 2.4601  | 3.2775  |
|             | Minimum     | 2.5620     | 1.4970  | 0.4557  | 0.3103   | 2.0367  | 2.0790  | 2.7467  |
|             | Std. Dev.   | 0.0468     | 0.0455  | 0.1331  | 0.0730   | 0.0676  | 0.1253  | 0.1950  |
|             | Skewness    | -2.4548    | 0.3469  | -0.0267 | 0.7623   | 0.3225  | 0.0806  | -0.0039 |
|             | Kurtosis    | 9.0183     | 2.1063  | 2.2564  | 2.5635   | 2.1847  | 1.5583  | 1.3457  |
|             | Jarque-Bera | 60.634     | 1.3336  | 0.8747  | 2.6199   | 1.1259  | 2.1920  | 2.8504  |
|             | Probability | 0.0000     | 0.5133  | 0.6457  | 0.2698   | 0.5695  | 0.3342  | 0.2404  |
|             | OP          | Mean       | 2.5706  | 2.1557  | 2.2000   | 1.8739  | 2.6219  | 1.5616  |
| Median      | 2.5473      | 2.1531     | 2.1956  | 1.9112  | 2.6658   | 1.5568  | 2.2406  |         |
| Maximum     | 2.7521      | 2.3389     | 2.2788  | 2.1356  | 2.7437   | 1.6322  | 2.3315  |         |
| Minimum     | 2.4803      | 1.9874     | 2.0840  | 1.5345  | 2.4812   | 1.4452  | 2.1524  |         |
| Std. Dev.   | 0.0760      | 0.1002     | 0.0524  | 0.1960  | 0.0984   | 0.0447  | 0.0565  |         |
| Skewness    | 1.0528      | 0.2996     | -0.3403 | -0.5094 | -0.3046  | -0.4752 | -0.0334 |         |
| Kurtosis    | 3.3713      | 2.2257     | 2.3959  | 1.9067  | 1.4313   | 3.1311  | 1.7621  |         |
| Jarque-Bera | 4.7623      | 0.9986     | 0.8628  | 2.3263  | 2.9498   | 0.3813  | 1.6007  |         |
| Probability | 0.0924      | 0.6069     | 0.6496  | 0.3124  | 0.2287   | 0.6436  | 0.4491  |         |
| GP          | Mean        | 2.7216     | 2.1392  | 1.5934  | 0.9529   | 2.7051  | 1.3871  | 1.6303  |
|             | Median      | 2.6943     | 2.1405  | 1.5913  | 0.9925   | 2.7126  | 1.4201  | 1.5865  |
|             | Maximum     | 2.8494     | 2.1902  | 1.7271  | 1.3249   | 2.7374  | 1.6468  | 2.0953  |
|             | Minimum     | 2.6656     | 2.0208  | 1.3795  | 0.5104   | 2.6662  | 1.1302  | 1.1667  |
|             | Std. Dev.   | 0.0565     | 0.0422  | 0.1137  | 0.2445   | 0.0222  | 0.1296  | 0.3281  |
|             | Skewness    | 1.1585     | -0.8911 | -0.3538 | -0.0479  | -0.1782 | -0.2727 | 0.0738  |
|             | Kurtosis    | 2.9263     | 3.6644  | 1.7615  | 1.9686   | 1.6123  | 2.9343  | 1.4872  |
|             | Jarque-Bera | 5.5987     | 3.7685  | 2.1191  | 1.1175   | 2.1382  | 0.3144  | 2.4064  |
|             | Probability | 0.0608     | 0.1519  | 0.3465  | 0.5719   | 0.3433  | 0.8545  | 0.3002  |
|             | PT          | Mean       | 5.2639  | 3.6056  | 2.8191   | 3.5515  | 4.3861  | 3.6062  |
| Median      | 5.2776      | 3.6219     | 2.7520  | 3.5972  | 4.3974   | 3.6035  | 4.8181  |         |
| Maximum     | 5.4703      | 3.7420     | 3.1348  | 3.7160  | 4.5965   | 4.1205  | 6.0809  |         |
| Minimum     | 4.9657      | 3.3857     | 2.5865  | 3.3222  | 4.1791   | 3.0824  | 4.0000  |         |
| Std. Dev.   | 0.1604      | 0.1026     | 0.1811  | 0.1188  | 0.0925   | 0.3457  | 0.7202  |         |
| Skewness    | -0.4347     | -0.8976    | 0.6221  | -0.4121 | -0.4168  | 0.0282  | 0.2051  |         |
| Kurtosis    | 1.9013      | 2.8819     | 1.9130  | 1.8578  | 3.2979   | 1.5682  | 1.6136  |         |
| Jarque-Bera | 2.0444      | 3.3720     | 2.8438  | 2.2106  | 0.8164   | 2.1387  | 2.1775  |         |
| Probability | 0.3597      | 0.1852     | 0.2412  | 0.3310  | 0.6648   | 0.3432  | 0.3336  |         |

Note: Abbreviations: Y = real per capita income; CO2 = carbon dioxide emissions. C.P. = production; O.P. = oil production; G.P. = natural gas production; and P.T. = total patent applications. All the considered variables are in the log forms.

**Table 2.** Results of the Pesaran's C.D. test.

|           | CO2     | Y       | Y <sup>2</sup> | CP      | OP      | GP      | PT      |
|-----------|---------|---------|----------------|---------|---------|---------|---------|
| Statistic | 6.9460* | 20.936* | 20.958*        | 2.5970* | 7.5210* | 12.158* | 16.516* |
| P-value   | 0.0000  | 0.0000  | 0.0000         | 0.0009  | 0.0000  | 0.0000  | 0.0000  |

Note: \*, denotes 1% significance level.

**Table 3.** Results of the panel unit root test.

|                | LLC     |                  | Breitung |                  | Decision |
|----------------|---------|------------------|----------|------------------|----------|
|                | Level   | First difference | Level    | First difference |          |
| CO2            | -1.6100 | -6.8692*         | 4.7070   | -4.7432*         | I (1)    |
| Y              | -0.9014 | -7.0499*         | 6.3084   | -3.0360*         | I (1)    |
| Y <sup>2</sup> | -0.4156 | -6.9098*         | 6.3917   | -3.8806*         | I (1)    |
| CP             | -1.9178 | -7.5061*         | 3.1011   | -4.4987*         | I (1)    |
| OP             | -3.5984 | -7.2134*         | 4.1653   | -2.4321*         | I (1)    |
| GP             | -2.2743 | -7.0813*         | 4.0020   | -3.3756*         | I (1)    |
| PT             | -0.7847 | -9.1194*         | 4.9605   | -4.7803*         | I (1)    |

Note: \* represent 1% level of significance, but no intercept and trend were used. L.L.C. = Levin et al. (2002) test; and Breitung = Breitung (2000) panel unit root tests.

**Table 4.** Results of the Kao panel co-integration unit root test.

| Cointegrations tests          | t-statistic | Prob.    |
|-------------------------------|-------------|----------|
| Augmented Dickey-Fuller (ADF) | -3.03227*   | (0.0012) |
| HAC variance                  | 0.000156    |          |
| Residual variance             | 0.000241    |          |

Note: \*represent the (rejection of the null hypotheses of no cointegration) at 1%.

**Table 5.** Results of long-term estimates

| Regressors     | D.F.E.       |         | M.G.         |         | P.M.G.       |         |
|----------------|--------------|---------|--------------|---------|--------------|---------|
|                | Coefficients | P-value | Coefficients | P-value | Coefficients | P-value |
| Y <sup>2</sup> | -0.5747      | 0.1340  | 0.64026      | 0.7830  | -0.1727*     | 0.0000  |
| Y              | 4.8753       | 0.1430  | -4.1160      | 0.8260  | 1.8876*      | 0.0000  |
| CP             | 0.26170      | 0.5880  | 0.22208      | 0.1420  | 0.3791*      | 0.0000  |
| OP             | 0.24973      | 0.5890  | -0.4240      | 0.2290  | 0.0615***    | 0.0890  |
| GP             | -0.21104     | 0.6860  | 0.42429      | 0.1610  | -0.0755**    | 0.0170  |
| PT             | -0.16617     | 0.6690  | 0.03784      | 0.4070  | 0.01244      | 0.7750  |
| ECT (-1)       | -0.04196     | 0.2000  | -0.66179*    | 0.0000  | -0.3184**    | 0.0150  |
| Hausman test   | 3.06         | 0.8010  | 2.38         | 0.8801  |              |         |

Note: \*, \*\* and \*\*\* specify significance level at 1 %, 5% and 10%.

CO2e by -0.075% in the long-term. This adverse relationship lends credence to prior findings (e.g., Alkhatlan, 2013) that natural gas production can be adopted as a more eco-friendly alternative to oil and coal production to reduce CO2e. The positive yet insignificant coefficient of innovation was somewhat surprising, yet in effect, Mensah et al. (2018) also observed mixed results for innovations in some OECD economies.

Furthermore, the positive coefficient of income per capita and the negative (significant) coefficient of income per capita (squared) suggested that the former contributes but the later disrupts CO2e: consequently, confirming the existence of the E.K.C. across all panels, consistent with prior findings (cf. Rahman & Ahmad, 2019; Sinha & Shahbaz, 2018). The negative and statistically significant coefficient of the E.C.T. (-0.31841) also provided support for cointegration, thereby confirming the long run association between CO2e and other explanatory variables. As indicated by present

results, the existence of dynamic stability (or long-term) relationship between variables is measured through the E.C.T. coefficient values, ranging between 0 and  $-2$  (Fromentin, 2017). A possible explanation for the highly significant coefficient is that the current sample includes the U.S. and China – top-ranking global economies vis-à-vis coal production, coal consumption, and CO<sub>2</sub>e. Reported estimates demonstrate that coal consumption has been consistently rising across the world: Russia (1.3%, 2017), India (18Mtoe, 2019), China (4Mtoe, 2019) and the world (1%, 2017) (BP, 2017). To conserve space, the result for short run estimates were excluded given that most variables output reflected insignificant signs, except for coal production.

## 5. Conclusion

This article has attempted to fill a critical knowledge gap in the economics literature by exploring the integrating energy production with energy consumption, income, and CO<sub>2</sub>e in the framework of the E.K.C. hypothesis for seven economies in B.R.I.C.S. and N.A.F.T.A. Using the P.M.G. estimator for the analyses of correction the panel data, the empirical results indicated that production of coal and oil has a positive and significant relationship with CO<sub>2</sub>e in all panels, while the coefficient of coal (significance at 1%) offered sufficient evidence to conclude that coal is one of the leading determinants of CO<sub>2</sub>e. This article also confirmed the existence of the E.K.C. hypothesis in the selected economies. Also, the impact of innovation on CO<sub>2</sub>e in the long-term was found to be insignificant, but natural gas production was found to have a mitigating impact on CO<sub>2</sub>e in the long-term.

The most important policy implications derived from current findings are as follows. First, the insignificant role of innovation asserts the need for governments to initiate more R&D investment in eco-innovation and cleaner technologies. Second, the adverse relationship of natural gas production with CO<sub>2</sub>e observed in this study reflect that the ongoing global focus on the natural gas exploration and consumption as an eco-friendly alternative to oil and coal has been rewarding. That said, the growth estimates for the consumption and production of coal and oil in 2019 in the developed and developing economies (e.g., the U.S., China, India, and Russia) are still alarming for global sustainability. Being the most influential stakeholders in the global energy, policymakers from these bi-polar economies must recognise their shared responsibility to collaborate more effectively in terms of disrupting the continually rising rate of global CO<sub>2</sub>e that affects not one but all. More precisely, there exists an imminent need to develop energy matrices at both regional and country level to bind, subsidise, and reward those economies that introduce and achieve shared renewable energy targets, invest in renewable energy resources, replace conventional with more eco-friendly energy sources, and invest in environment-focused R&D.

Indeed, the present work suffers from certain limitations stated henceforth. First, the empirical analyses are based on not all but few of the top energy-producing economies. Researchers are encouraged to address this limitation by examining other oil-rich economies in the Middle East and Africa, although the unavailability of data for different energy sources, especially coal production, can prove to be challenging. Second, the article examined the role of energy production at the disaggregate level of

analysis with primary energy sources (gas, oil, and coal) rather than aggregate level only. Future research is expected to extend the present framework through other sources of energy, e.g., wind, solar, biomass, electricity, and nuclear. Finally, researchers are also encouraged to test the current model for single-country analysis using various econometric techniques.

## References

- Ahmad, A., Zhao, Y., Shahbaz, M., Bano, S., Zhang, Z., Wang, S., & Liu, Y. (2016). Carbon emissions, energy consumption, and economic growth: An aggregate and disaggregate analysis of the Indian economy. *Energy Policy*, 96, 131–143. doi:10.1016/j.enpol.2016.05.032
- Ahmad, M., Hengy, H., Rahman, Z. U., Khan, S., Khan, Z. U., & Khan, Z. (2018). Carbon emissions, energy use, gross domestic product, and total population in China. *Ekonomia I Środowisko*, 2(65), 33–44.
- Ahmad, M., Hengy, H., Rahman, Z. U., Khan, S., Khan, Z. U., & Khan, Z. (2018). Impact of environmental quality variables and socio-economic factors on human health: Empirical evidence from China. *Pollution*, 4(4), 571–579. doi:10.22059/poll.2018.252214.391
- Ahmad, M., Khan, Z., Rahman, Z. U., & Khan, S. (2018). Does financial development asymmetrically affect CO2 emissions in China: An application of nonlinear autoregressive distribution lag (NARDL) model. *Carbon Management*, 9(6), 631. doi:10.1080/17583004.2018.1529998
- Alam, M. M., Murad, M. W., Md Noman, A. H., & Ozturk, I. (2016). Relationships among carbon emissions, economic growth, energy consumption, and population growth: Testing environmental kuznets curve hypothesis for Brazil, China, India, and Indonesia. *Ecological Indicators*, 70, 466–479. doi:10.1016/j.ecolind.2016.06.043
- Alkhatlan, K. A. (2013). The Nexus between remittance outflows and growth: A study of Saudi Arabia. *Economic Modelling*, 33, 695–700. doi:10.1016/j.econmod.2013.05.010
- Appiah, M. O. (2018). Investigating the multivariate granger causality between energy consumption, economic growth, and CO2 emissions in Ghana. *Energy Policy*, 112, 198–208. doi:10.1016/j.enpol.2017.10.017
- Azevedo, V. G., Sartori, S., & Campos, L. M. S. (2018). CO2 emissions: A quantitative analysis among the BRICS nations. *Renewable and Sustainable Energy Reviews*, 81, 107–115. doi:10.1016/j.rser.2017.07.027
- Baek, J. (2016). A new look at the FDI-income-energy-environment Nexus: Dynamic panel data analysis of ASEAN. *Energy Policy*, 91, 22–27. doi:10.1016/j.enpol.2015.12.045
- Boutabba, M. A. (2014). The impact of financial development, income, energy and trade on carbon emissions: Evidence from the Indian Economy Mohamed Amine Boutabba. *Economic Modelling*, 40, 33–41 doi:10.1016/j.econmod.2014.03.005
- BP. (2017). BP statistical review of world energy June 2017, no. June, 52. <http://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/statistical-review-2017/bp-statistical-review-of-world-energy-2017-full-report.pdf>.
- Breitung, J. (2000). The local power of some unit root tests for panel data. In Baltagi B (Ed.), *Nonstationary panels, panel cointegration, and dynamic panels, advances in econometrics* (vol. 15, pp. 161–178). Amsterdam: JAI.
- Chandia, K. E., Gul, I., Aziz, S., Sarwar, B., & Zulfikar, S. (2018). An analysis of the association among carbon dioxide emissions, energy consumption and economic performance: An econometric model” 3004 (May). *Taylor & Francis*. <https://doi.org/10.1080/17583004.2018.1457930>.
- Chen, P. Y., Chen, S. T., Hsu, C.-S., & Chen, C. C. (2016). Modeling the global relationships among economic growth, energy consumption, and CO2 emissions. *Renewable and Sustainable Energy Reviews*, 65, 420–431. <https://doi.org/10.1016/j.rser.2016.06.074>.
- Churchill, S. A., Inekwe, J., & Smyth, R. (2019). R & D Intensity and Carbon Emissions in the G7: 1870-2014, no. December 2018. <https://doi.org/10.1016/j.eneco.2018.12.020>.

- Danish, Z. B., Wang, Z., & Wang, B. (2017). Energy production, economic growth, and CO2 emission: Evidence from Pakistan. *Nat Hazards*, 90, 27–50. <https://doi.org/10.1007/s11069-017-3031-z>
- Dogan, E., & Aslan, A. (2017). Exploring the relationship among CO2 emissions, real GDP, energy consumption, and tourism in the EU and candidate countries: Evidence from panel models robust to heterogeneity and cross-sectional dependence. *Renewable and Sustainable Energy Reviews*, 77, 239–245. doi:10.1016/j.rser.2017.03.111
- Dogan, E., & Turkekul, B. (2015). Research article CO2 emissions, real output, energy consumption, trade, urbanization, and financial development: Testing the EKC hypothesis for the USA. <https://doi.org/10.1007/s11356-015-5323-8>.
- Esso, L. J., & Keho, Y. (2016). Energy consumption, economic growth, and carbon emissions: Cointegration and causality evidence from selected African Countries. *Energy*, 114, 492–497. doi:10.1016/j.energy.2016.08.010
- Farhani, S., Chaibi, A., & Rault, C. (2014). CO2 emissions, output, energy consumption, and trade in Tunisia. *Economic Modelling*, 38, 426–434. doi:10.1016/j.econmod.2014.01.025
- Fromentin, V. (2017). The long-run and short-run impacts of remittances on financial development in developing countries. *The Quarterly Review of Economics and Finance*, 66, 192–201. doi:10.1016/j.qref.2017.02.006
- Ghosh, S. (2010). Examining carbon emissions economic growth Nexus for India: A multivariate cointegration approach. *Energy Policy*, 38(6), 3008–3014. doi:10.1016/j.enpol.2010.01.040
- Hasan, I., & Tucci, C. L. (2010). The innovation – economic growth Nexus: Global evidence. *Research Policy*, 39(10), 1264–1276. doi:10.1016/j.respol.2010.07.005
- Hausman, J. (1978). Specification tests in econometrics. *Econometrica*, 46(6), 1251–1272. doi:10.2307/1913827
- Jalil, A., & Mahmud, S. F. (2009). Environment Kuznets curve for CO2 emissions: A cointegration analysis for China. *Energy Policy*, 37(12), 5167–5172. doi:10.1016/j.enpol.2009.07.044
- Kahia, M., Safouane Ben Aissa, M., & Lanouar, C. (2017). Renewable and non-renewable energy use - economic growth Nexus: The case of MENA net oil importing countries. *Renewable and Sustainable Energy Reviews*, 71, 127–140. doi:10.1016/j.rser.2017.01.010
- Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics*, 90(1), 1–44. doi:10.1016/S0304-4076(98)00023-2
- Kasman, A., & Selman Duman, Y. (2015). CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: A panel data analysis. *Economic Modelling*, 44, 97–103. doi:10.1016/j.econmod.2014.10.022
- Khan, Z., Sisi, Z., & Siqun, Y. (2018). Environmental regulations an option: Asymmetry effect of environmental regulations on carbon emissions using non-linear ARDL. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*. Taylor & Francis, 1–19. doi:10.1080/15567036.2018.1504145
- Kiviyiro, P., & Arminen, H. (2014). Carbon dioxide emissions, energy consumption, economic growth, and foreign direct investment: Causality analysis for sub-Saharan Africa. *Energy*, 74 (C), 595–606. doi:10.1016/j.energy.2014.07.025
- Levin, M., Lin, C. F., & Chu, C. S. (2002). Unit root tests in panel data: Asymptotic and finite sample properties. *Journal of Econometrics*, 108(1), 1. doi:10.1016/S0304-4076(01)00098-7
- Mensah, C. N., Long, X., Boamah, K. B., Bediako, I. A., Dauda, L., & Salman, M. (2018). The effect of innovation on CO2 emissions of OCED Countries from 1990 to 2014. *Environmental Science and Pollution Research*, 25(29), 29678–29698. doi:10.1007/s11356-018-2968-0
- Mirza, F. M., & Kanwal, A. (2017). Energy consumption, carbon emissions, and economic growth in Pakistan: Dynamic causality analysis. *Renewable and Sustainable Energy Reviews*, 72, 1233. (October 2016). doi:10.1016/j.rser.2016.10.081
- Mohiuddin, O., Asumadu-Sarkodie, S., & Obaidullah, M. (2016). The relationship between carbon dioxide emissions, energy consumption, and GDP: A recent evidence from Pakistan energy consumption, and GDP: A recent evidence. *Cogent Engineering*, 1(1), 1–16. doi:10.1080/23311916.2016.1210491

- Obradović, S., & Lojanica, N. (2017). Energy use, CO2 emissions, and economic growth – causality on a sample of SEE Countries. *Economic Research-Ekonomska Istraživanja*, 30(1), 511–526. doi:10.1080/1331677X.2017.1305785
- Ozturk, I., & Acaravci, A. (2013). The long-run and causal analysis of energy, growth, openness, and financial development on carbon emissions in Turkey. *Energy Economics*, 36, 262–267. doi:10.1016/j.eneco.2012.08.025
- Pao, H. T., & Tsai, C. M. (2011). Multivariate granger causality between CO2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China). *Energy*, 36(1), 685–693. doi:10.1016/j.energy.2010.09.041
- Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels general diagnostic tests for cross section dependence in panels. Univ. Cambridge. <https://www.repository.cam.ac.uk/bitstream/handle/1810/446/cwpe0435.pdf?sequence=1&isAllowed=y>
- Pesaran, M. H., Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 94(446), 621. doi:10.1080/01621459.1999.10474156
- Rahman, Z. U., Hongbo, C., & Ahmad, M. (2019). A new look at the remittances-FDI-energy-environment nexus in the case of selected Asian nations. *The Singapore Economic Review*. doi:10.1142/S0217590819500176
- Rahman, Z. U., & Ahmad, M. (2019). Modeling the relationship between gross capital formation and CO2 (a) symmetrically in the case of Pakistan: An empirical analysis through NARDL approach. *Environmental Science and Pollution Research*, 26(8), 8111. doi:10.1007/s11356-019-04254-7
- Saboori, B., Sulaiman, J., & Mohd, S. (2012). Economic growth and CO2 emissions in Malaysia: A cointegration analysis of the environmental Kuznets curve. *Energy Policy*, 51, 184–191. doi:10.1016/j.enpol.2012.08.065
- Salim, R. A., & Ra, S. (2012). “Why do some emerging economies proactively accelerate the adoption of renewable energy?” 34, 1051–1057. doi:10.1016/j.eneco.2011.08.015
- Shahbaz, M., Adnan Hye, Q. M., Kumar Tiwari, A., & Leitão, N. C. (2013). Economic growth, energy consumption, financial development, international trade, and CO2 emissions in Indonesia. *Renewable and Sustainable Energy Reviews*, 25, 109–121. doi:10.1016/j.rser.2013.04.009
- Shahbaz, M., Shahzad, S. J. H., & Mahalik, M. K. (2017). Is globalization detrimental to CO2 emissions in Japan? New threshold analysis. *Environmental Modeling & Assessment*, 1–12. doi:10.1007/s10666-017-9584-0
- Sharma, S. S. (2011). Determinants of carbon dioxide emissions: Empirical evidence from 69 Countries. *Applied Energy*, 88(1), 376–382. doi:10.1016/j.apenergy.2010.07.022
- Sinha, A., & Shahbaz, M. (2018). Estimation of environmental Kuznets curve for CO2 emission: Role of renewable energy generation in India. *Renewable Energy*, 119, 703–711. doi:10.1016/j.renene.2017.12.058
- Tamazian, A., Chousa, J. P., & Vadlamannati, K. C. (2009). Does higher economic and financial development lead to environmental degradation: Evidence from BRIC Countries. *Energy Policy*, 37 (1), 246–253. doi:10.1016/j.enpol.2008.08.025
- Wang, S., Li, G., & Fang, C. (2017). Urbanization, economic growth, energy consumption, and CO2 emissions: Empirical evidence from Countries with different income levels. *Renewable and Sustainable Energy Reviews*. doi:10.1016/j.rser.2017.06.025
- Wang, Y., Chen, L., & Kubota, J. (2016). The relationship between urbanization, energy use, and carbon emissions: Evidence from a panel of association of Southeast Asian Nations (ASEAN) Countries. *Journal of Cleaner Production*, 112, 1368–1374. doi:10.1016/j.jclepro.2015.06.041
- World Development Indicators WDI. (2018). World Bank, 2018. <http://datatopics.worldbank.org/world-development-indicators/>. Accessed 6 June 2018.
- Zaman, K., Khan, A., & Rusdi, M. (2016). Dynamic linkages among energy consumption, environment, health and wealth in BRICS Countries: Green growth key to sustainable

- development dynamic linkages among energy consumption, environment, health and wealth in BRICS Countries: Green growth key to sustainable development. *Renewable and Sustainable Energy Reviews*, 56, 1263–1271. (February 2018). doi:[10.1016/j.rser.2015.12.010](https://doi.org/10.1016/j.rser.2015.12.010)
- Zhang, B., & Wang, Z. (2017). Energy production, Economic growth, and CO2 emission: Evidence from Pakistan. *Natural Hazards*, 90(1), 27–50. doi:[10.1007/s11069-017-3031-z](https://doi.org/10.1007/s11069-017-3031-z).
- Zhang, X. P., & Cheng, X. M. (2009). Energy consumption, carbon emissions, and economic growth in China. *Ecological Economics*, 68(10), 2706–2712. doi:[10.1016/j.ecolecon.2009.05.011](https://doi.org/10.1016/j.ecolecon.2009.05.011)
- Zhu, H., Duan, L., Guo, Y., & Yu, K. (2016). The effects of FDI, economic growth, and energy consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression. *Economic Modelling*, 58, 237–248. doi:[10.1016/j.econmod.2016.05.003](https://doi.org/10.1016/j.econmod.2016.05.003)
- Zoundi, Z. (2017a). CO2 emissions, renewable energy, and the environmental Kuznets curve, a panel cointegration approach. *Renewable and Sustainable Energy Reviews*, 72, 1067–1075. doi:[10.1016/j.rser.2016.10.018](https://doi.org/10.1016/j.rser.2016.10.018)
- Zoundi, Z. (2017b). CO2 emissions, renewable energy, and the environmental Kuznets curve, a panel cointegration approach. *Renewable and Sustainable Energy Reviews*, 72, 1067–1075. doi:[10.1016/j.rser.2016.10.018](https://doi.org/10.1016/j.rser.2016.10.018)