Economic Research-Ekonomska Istraživanja

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rero20

Novel research methods to examine renewable energy and energy related greenhouse gases: evidence from novel panel methods

Chao Zhang & Ziwei Zhang

To cite this article: Chao Zhang & Ziwei Zhang (2023) Novel research methods to examine renewable energy and energy related greenhouse gases: evidence from novel panel methods, Economic Research-Ekonomska Istraživanja, 36:1, 1187-1204, DOI: 10.1080/1331677X.2022.2082998

To link to this article: https://doi.org/10.1080/1331677X.2022.2082998

Published online: 08 Jun 2022.

ECONOMIC RESEARCH-EKONOMSKA ISTRAŽIVANJA
2023, VOL. 36, NO. 1, 1187–1204
https://doi.org/10.1080/1331677X.2022.2082998

Novel research methods to examine renewable energy and energy related greenhouse gases: evidence from novel panel methods

Chao Zhang[a] and Ziwei Zhang[b]

[a]School of Public Management, Liaoning University, Shenyang, China; [b]School of Economics, Liaoning University, Shenyang, China

ABSTRACT

In the current time, the most distressing issue is emissions control and environmental recovery. All developed and developing economies are rapidly expanding their industrial sector and increasing energy use while struggling for environmental sustainability. This study aims to analyse whether renewable energy helps BRICS economies reduce energy related emissions. Also, the role of economic growth, research and development, and public–-private partnership investment in energy is investigated during the period from 1990 to 2020. Using various panel data instruments, the results illustrate the slopes heterogeneity, panel cross-section dependence, and the long-run co-integration association between the variables. Using the novel method of moment quantile regression, this study found that economic growth adversely affects environmental quality by triggering energy related emissions. However, renewable energy consumption, research and development, and public–private partnership investment in energy significantly reduce energy related emissions in the region at all quantile (25th, 50th, 75th and 90th). Besides, this study found bidirectional causal nexus between economic growth, renewable energy, research and development, and the energy related greenhouse gas emissions, while unidirectional causality from public–-private partnership investment to energy related emissions. Some relevant policies are suggested that could help tackle the issue of energy related emissions.

ARTICLE HISTORY
Received 30 March 2022
Accepted 23 May 2022

KEYWORDS
Novel research methods; energy related emissions; renewable energy; economic growth; research and development; public–private partnership; method of moment quantile regression

JEL CODES
F64; K32; P18

1. Introduction

Sustainable development demonstrates balancing the requirements of the present population without depleting resources for future generations. In other terms, sustainable development seeks to preserve the natural environment for future generations (s) while still satisfying increasing demands (Gyamfi et al., 2018). The history of sustainable development is based on the World Commission on Environment and

CONTACT Ziwei Zhang ziweilnu@163.com

Development's (WCED) 1987 Brundtland Report Our Common Future, which stated that raising energy usage, population, and extreme utilization of natural resources are the main hurdles sustainable development. The committee also underlined that economic development alone is insufficient for sustainability and that reduced resource and energy consumption is required (Brundtland & Khalid, 1987). We hope that our research will add to the ongoing discussion over sustainability. In this regard, our research focuses on the impact of renewable energy consumption, and economic growth, research and development expenditures, and public–private partnership investment in energy on environmental deterioration and particularly on the energy-related greenhouse gas emission in BRICS nations (Brazil, Russia, India, China, and South Africa). In emerging nations, the globalization movement is characterized by a sharp rise and diversity of consumption and production. Because fossil fuels in the manufacturing of commodities contributes to environmental deterioration and endangers human health, countries are shifting to renewable energy sources such as wind and solar, which may not cause pollution and are abundant in nature.

The world's highest temperatures during the preceding years demonstrate the magnitude of global warming. Carbon emissions, which peaked in 2019 at roughly 34,169 million tons, are the major contribution to GHGs (BP, 2020). In 2017, carbon emissions rose to 405.5 parts per million (ppm), methane gas risen significantly to 1859 parts per billion (ppb), and nitrogen dioxide emissions increased to 329.9 ppb, depicting increases of 146%, 257%, and 122%, respectively, compared to the pre-industrial times (WMO, 2019). Other environmental contaminants, in addition to carbon emissions, have a substantial impact on global warming and climate change (Yilanci & Pata, 2020). As growing pollutants produce environmental issues such as climate change and global warming, which severely impact human health and national economies, it is critical to identify the elements driving environmental degradation indicators. Economic growth, renewable energy, research and development, and public–private partnership investment are four essential elements influencing sustainable development and environmental deterioration.

In 2018, the BRICS nations' total population was roughly 3.16 billion, accounting for 41.57% of the world population, providing appropriate labour protection for BRICS countries (World Bank, 2018). China, Russia, South Africa, India, and Brazil have large labour populations. The workforce population in India and China has been very beneficial to economic progress. According to the BRICS nations' natural population growth rates, Russia and South Africa are growing natural population growth rates; China and India are huge economies with more than 1.3 billion people. This means that energy and other natural resources will be used much more in this area. The BRICS nations' significance in the global economy is growing. As per statistics from the World Bank, the BRICS nations contributed 51.3% of global economic growth from 2008 to 2018, making them a major engine of global economic development. During 2008–2018, the BRICS nations' nominal GDP grew from 11.8% to 22.3% of global GDP (World Bank, 2018). Whereas the BRICS nations' total GDP in 2017 was 188.76 billion US dollars, accounting for 23.3% of the global total. However, as the economy grows, the degree of public–private partnership investment, research and development expenditure, and renewable energy usage rise for various economic and, most importantly, environmental reasons. As a result, this research tends to draw decision-makers attention to this generally overlooked sector, especially in developing countries.

The primary objective of this research is to examine whether renewable energy consumption could influence the energy-related greenhouse gas emissions. As mentioned in the literature, the earlier studies extensively studied the association of renewable energy and carbon emissions. However, the association between renewables and energy related emissions is still scant and particularly in case of the BRICS economies. Since the BRICS economies are emerging economies paying more attention towards the development of economic growth. However, the economic growth is reported rapidly increasing over the last few years. Nonetheless, most of the existing studies have demonstrated that economic growth is encouraging carbon emissions (Shahbaz et al., 2020; Li & Li, 2020). Still, the image is unclear regarding the influence of economic growth on energy related emissions, particularly in the BRICS economies. Therefore, this could be a novel contribution to the existing studies that provide empirical evidence regarding this specific influence in the case of the BRICS economies. Besides, the developed economies are more concerned about increasing research and development expenditure and public–private partnership investment in energy to tackle environmental issues like climate change, global warming, and environmental degradation. However, the developing and emerging economies like BRICS are more growth oriented and are heavily dependent on the industrial sector where the traditional fossil fuel energy is consumed excessively. Therefore, this study also aims to analyse whether research and development expenditure, and public–private partnership investment in energy help reducing energy related emissions in these economies. Hence, this could be the first attempt to analyse the true relationship of these variables with the specific energy related greenhouse gas emissions in the case of the BRICS economies for innovative and relevant policy measures to attain sustainable development and a low carbon economy.

The manuscript is further classified into four sections: Section 2 embodied relevant literature review of literature, covering all the concerned variables; Section 3 depicts data and methodology used for empirical analysis; Section 4 covers empirical results and discussion; Section 5 provides conclusion and policy implications suggested based on empirical findings.

2. Literature Review

This section is classified into two sub-sections. First sub-section briefs about the empirical evidence on energy-related methane emissions and renewable energy consumption. The second sub-section elaborates on the corresponding empirical shreds of evidence on renewable energy output, R&D expenditures, and public-private investments documented in the prevailing literature that are summarized.

2.1. Energy-related methane emissions and renewable energy consumption

The literature on Energy-related methane emissions and renewable energy consumption is scarce. However, studies have examined the negative linkage of greenhouse and methane emissions with the economic development of countries. Subsequent empirical pieces of evidence clarify the association between the aforementioned variables. The cumulative population growth around the world has triggered rapid methane emissions. The main causes include fossils combustion and natural gas leakage, which severely impact climate change (Rehman et al., 2020). The Global Methane Initiative (2004) suggested that every country plan and strategize policies to reduce these emissions. Renewable energy consumption is an effective and efficient solution for environmental concerns and sustainable development (Dincer, 2000). Renewable energy sources and green technologies play a significant role in mitigating methane emissions (Daloglu). Endorsing renewable energy usage helps unravel environmental crises. Clean green efficient renewable technologies help in climate change and emissions (CH4 and GHG) along with other pollutants (Baskutis et al., 2021) and (Assi et al., 2021). Methane emissions are strong and more powerful than the greenhouse gas emissions nearly responsible for (0.5o C) global warming. Its concentrations have been increased twofold since the pre-industrial eras (Climate action network, 2021). The methane emissions are tripled from the period 1980 to 2007 in China. The major sources were coal mining, biofuel combustion, and natural gas leakage that escalated the emissions to 548.6 Mt CO2-eq in 2007 (Zhang et al., 2014). While approximately 75% of GHG and CH4 emissions in 2012 occurred due to the manufacturing sector that needs effective actions (Zhang et al., 2020). Methane emissions are commonly known as agriculture-based emissions caused by fertilizers, urea, etc. (Reisinger et al., 2021). Several authors considered limiting energy-related greenhouse emissions (methane) through renewable energy consumption. El-Fadel et al. (2003) described that almost 90% of methane emissions were reduced by utilizing renewable energy like biomass, solar, wind, or hydropower in Lebanon. Australia is also investigating potential sources of renewable energy alternatives that will reduce the harmful GHG emissions (Yusaf et al., 2011). Charabi (2021) studied Oman as Gulf Cooperation Council Country (GCC) for exploring methane emission reduction policies. The author suggested that the emissions almost increased twice times from 2000 to 2015. Efficient abatement policies play a vital role in mitigating emissions. Few authors have confirmed the recycling of carbon dioxide in the form of methane for renewable energy production. Due to the increasing exhaustion of energy sources, this can be an alternative way for acquiring energy without being reliant on fossil/fissile resources (Hashimoto et al., 2014). Frank et al. (2012) exploited algal biofuels for limiting greenhouse emissions of which 14% are methane emissions. Utilizing renewable energy helps in reducing emissions. In the case of China, Yongjun et al. (2021) demonstrated the catalytic reduction of emissions utilizing methanol fuel. Academicians and environmentalists have energy-related emissions reductions strategies and policies to reduce these emissions. They are expected to achieve the lowest possible carbon emissions by 2030 (Borba et al., 2012).

2.2. Does renewable energy output, R&D expenditures, and public–private investments influence methane emissions?

Khan et al. (2021) indicated the inverse influence of renewable energy on environmental degradation. Economic activities or the Gross domestic product (GDP) negatively influence environmental pollution. They insisted that increasing electricity output and renewable energy consumption decreases carbon emissions. The research and development expenditures in the case of OECD economies demonstrated the mixed impact of R&D on methane and nitrous emissions. The average impact is negative, while the individual impact of emissions is positive for at least 40% of the economies (Petrović & Lobanov, 2020). On the other hand, recent studies demonstrate that a higher level of economic growth enhances the emissions level in the country or region (Li & Li, 2020; Shahbaz et al., 2020). These studies demonstrate that enhancement in economic growth is linked to the excessive use of fossil fuel consumption, which causes environmental degradation via increasing emissions level. Moreover, Saidi and Omri (2020) asserted that a bidirectional causal association exists between economic growth and emissions. Wan et al. (2022) foretold inverse association of R&D and carbon dioxide emissions. Due to increasing income inequality, energy consumption falls, increasing research and development expenses and carbon emissions. They studied 217 economies from 1960 till date. Shahbaz et al. (2018) utilized research & development as a proxy for energy funds and found increasing the funds for energy reduces harmful emissions. Cheng et al. (2021) investigated the impact of public and private investments from 1991Q1 to 2017Q4 in China over the carbon neutrality targets. They concluded that public-private investments in energy increase carbon emissions, whereas renewable energy negatively affects emissions. Another study analyzed the causal relationship between public-private investment and carbon emissions. Raza et al. (2021) confirmed no Granger casual association though some non-linear association exists among the variables. They determined that public-private investments in the non-renewable sector degrade the environment while investing in renewable energy improves the environment. Further, in India, public–private investments and renewable energy significantly impact carbon emissions. The findings showed that increasing renewable investment provides a sustainable environment (Kirikkaleli & Adebayo, 2021). Moreover, in general, the relationship between renewable energy consumption and economic growth (GDP) is bidirectional (Mardani et al., 2019) and (Radmehr et al., 2021). However, the empirical findings in case of Oil Exporting economies (OPEC) throughout 1995–2012, Tarazkar et al. (2021) depicted an N-shaped connotation between the gross domestic product of the economy and methane emissions, indicating a constructive (positive) association. Previous literature is focused on examining the role of renewable energy consumption in the environment and economic development. The prior studies ignored the Energy-related methane emissions influence on renewable energy consumption. The current research bridges the gap by introducing novel explanatory factors like Renewable electricity output, GDP, Research and development expenditure, and public–private partnerships investment in energy, for examining the impact on methane emissions. The present study also fills the gap by exploring the influence of methane emissions and renewable energy in the case of BRICS economies.

3. Data and Methodology

Based on the objective and literature given above, this study uses energy related methane emissions as a percent of total emissions. This variable is used as a focused variable that captures energy-related greenhouse gas emissions (*ERGHG*) because most of the emissions are energy-related and release from the industrial sector while using non-renewable energy sources (Shahbaz et al., 2020). However, these energy sources are utilized to fulfil energy requirements and achieve sustained economic growth (*GDP* : measured in constant 2015 US$) (Li & Li, 2020). Therefore, this study tends to examine whether *GDP* affect *ERGHG*. On the other hand, countries adopted various measures to reduce emissions. Specifically, renewable energy consumption (*REC* : measured as percent of total final energy consumption), research and development (*R&D* Percent of *GDP*) and public–private partnerships investment in energy (*PPIE* : measured in the current US$) are used to control emissions (Baskutis et al., 2021; Wan et al., 2022; Kirikkaleli & Adebayo, 2021). Data for the said variables are obtained from the World Bank (2020)[1], while covering the last three decades, 1990–2020 for the BRICS economies including Brazil, Russia, India, China, and South Africa. Following the study of Khan et al. (2021), this study constructed the model given as:

$$ERGHG_{it} = f(GDP_{it}, REC_{it}, R\&D_{it}, PPIE_{it})$$

However, the above-mentioned model could adopt the following regression form for empirical examination:

$$ERGHG_{it} = \alpha_1 + \beta_1 GDP_{it} + \beta_2 REC_{it} + \beta_3 R\&D_{it} + \beta_4 PPIE_{it} + \varepsilon_{it} \quad (1)$$

The Eq. (1) indicates that *ERGHG* is the energy related greenhouse gas emissions, while *GDP*, *REC*, *R&D* and *PPIE* is economic growth, renewable energy consumption, research and development, and public–private partnerships investment in energy, respectively. Besides, α and $\beta's$ are intercepts and slopes, respectively. Whereas ε is the random error term of the regression model. Moreover, '*i*' and '*t*' in the subscript denotes cross-sections and time series accordingly.

3.1. Estimation Techniques

3.1.1. Descriptive Statistics and Normality

This research employs descriptive statistics to summarize data before estimating data empirically. This section analyses each variable's mean, median, maximum, and minimum values, where the latter indicates the range of observations. We also calculate the standard deviation, which shows the variation of a variable from the mean. In addition, this research also utilizes skewness and Kurtosis to assess the data's uniformity, contrasting this with the broader examination of data normalcy. In this regard, we used Jarque and Bera (1987) (JB) normalcy test, which operates as follows:

$$JB = \frac{N}{6}\left(S^2 + \frac{(K-3)^2}{4}\right), \quad (2)$$

In the equation, 'N' represents the number of observations, 'S' skewness, and 'K' excess Kurtosis. This test is more helpful than skewness and Kurtosis assessments since it measures both at the same time. A JB test's null hypothesis states that both estimates are zero, showing the normality of the data. However, the proposition could be rejected if the predicted findings are significant at any level of significance, showing abnormal variables' distributions.

3.1.2. Testing Slope Heterogeneity and Cross-Section Dependence

This research explores panel data properties such as slope coefficient heterogeneity (SCH) and panel cross-section dependency (PCD). Globalization and trade intensified between 1760 and 1840, causing certain economies to specialize in specific goods and services while others specialized in varying goods and services. Because of this phenomenon, some economies depend on other regions and states to meet technological, economic, environmental, and financial objectives. As a result of this dependency, governments developed measures that may cause economies to resemble one another, raising the issue of slope homogeneity, an econometric issue. As a result, panel data estimates may be unproductive and inaccurate (Breitung, 2005; Le & Bao, 2020). The problem is solved using Pesaran and Yamagata (2008) SCH. This test is efficient since it offers both the SCH and the adjusted SCH (ASCH) adopted the following forms:

$$\hat{\Delta}_{SCH} = \sqrt{N(2k)^{-1}}(N^{-1}\acute{\text{S}} - \text{K}) \tag{3}$$

$$\hat{\Delta}_{ASCH} = \sqrt{N}\sqrt{\frac{T+1}{2K.(T-K-1)}}(N^{-1}\acute{\text{S}} - 2\text{K}), \tag{4}$$

where $\hat{\Delta}_{SCH}$ is the slope coefficient homogeneity specified in Eq. (3), and $\hat{\Delta}_{SCH}$ is the adjusted slope coefficient homogeneity in Eq. (4). The null hypothesis also asserts that slope coefficients are homogenous until significant.

Since globalization and cross-border competition and trade allow countries to specialize in commodities and/or services, which are in high demand internationally, As a result, these economies become more and more reliant on the specialized ones. Disregarding the PCD problem may result in conflicting conclusions in the exploratory research (Campello et al., 2019). Therefore, we apply Pesaran's (2021) PCD test to see whether the chosen economies are cross-sectionally dependent. The cross-sectional dependency expression is:

$$\text{CD}_{Test} = \frac{\sqrt{2T}}{[N(N-1)]^{1/2}}\sum_{i=1}^{N-1}\sum_{k=1+i}^{N} T_{ik}, \tag{5}$$

The test's null assumption shows that cross-sections are not dependent on one another. Significant estimations are required to reject the null hypothesis and demonstrate cross-sectional dependence.

3.1.3. Unit Root

To address the SCH and PCD, the panel data concerns, the present investigation may use an estimate that accommodates the issues mentioned above. As a result, we incorporated Pesaran's (2007) cross-sectional IPS (*CIPS*). Initially, Pesaran (2006) proposed factor modelling to account for cross-sectional dependence. Cross-sectional means are calculated as unexplained components using this tool. Pesaran (2007) extends the *ADF* regression by including the model's mean and first difference of lag cross-sections. This approach tackles cross-section dependency even if the panel is imbalanced (i.e., $T > N$ or $N > T$). The cross-section *ADF* has the following mathematical form:

$$\Delta y_{i,t} = \theta_i + \beta_i^* y_{i,t-1} + d_0 \bar{y}_{t-1} + d_1 \Delta \bar{y}_t + \varepsilon_{it} \tag{6}$$

As indicated above, $\bar{y}_t$ represents the N observations' average value. To compensate for serial correlation, the above equation might be supplemented by the inclusion of $\bar{y}_t$ and y_{it}' s first difference lags, such as:

$$\Delta y_{it} = \theta_i + \beta_i^* y_{i,t-1} + d_0 \bar{y}_{t-1} + \sum_{j=0}^{n} d_{j+1} \Delta \bar{y}_{t-j} + \sum_{k=1}^{n} c_k \Delta y_{i,t-k} + \varepsilon_{it}, \tag{7}$$

As a consequence, by averaging the t-statistics for a specific unit of cross-sectional data, the Pesaran (2007) *CIPS* can be assessed in selected panel economies (*CADFi*). The *CIPS* in the equation form is as follows:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i, \tag{8}$$

The existence of a unit root in the time series is often used as an assumption in the (*CIPS*) test.

3.1.4. Co-integration Testing

The error correction model (ECM) developed by Westerlund (2007) is used to evaluate the long-run equilibrium relationship of variables in BRICS economies in this paper. In the presence of cross-sectional dependency and slope heterogeneity, this test gives reliable estimates by integrating the mean of the group and the statistics from the panel. The preceding is a commonly used approach of analysing both statistics and is shown as: $G_\tau = \frac{1}{N}\sum_{i=1}^{N} \frac{\hat{\alpha}_i}{S.E\hat{\alpha}_i}$, and $G_a = \frac{1}{N}\sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)}$, evaluates the mean group estimates, whereas, $P_\tau = \frac{\hat{\alpha}}{S.E(\widehat{\alpha})}$, and $P_a = T.\hat{\alpha}$, are used for panel estimates.

3.1.5. Method of Movement Quantile Regression (MMQR)

Panel quantile regression, first proposed by Koenker and Bassett (1978), computes dependent mean and conditional variance relying on explanatory variable values. When the dataset possesses irregular distribution patterns, quantile regression delivers accurate results. Due to this unequal data distribution, we used Machado and Silva (2019) novel method of moments quantile regression (MMQREG). The distributional and diverse features of quantile numbers are investigated using this unique technique (Sarkodie & Strezov, 2019). To calculate the conditional quantile location-scale $Q_y(\tau|R)$ variant, the following formula could be used:

$$Y_{it} = \theta_i + \vartheta R_{it} + (\delta_i + \rho \acute{Z}_{it})\mu_{it}., \tag{9}$$

Here, Eq. (9) shows that the probability $p(\delta_i + \rho.\acute{Z}_{it} > 0)$ is equal to one. However, the estimated coefficients are θ, ϑ, δ, and ρ. Besides, 'i' in the subscript reveals fixed effect as offered by θ_i and δ_i, where $i = 1, 2, \ldots, n$. While k-vector is the standard element of R – denoted by Z, which is a unique alteration showed by the component $\lessdot$, and presented as:

$$Z_{\lessdot} = Z_{\lessdot}(R), \ \lessdot = 1, 2, \ \ldots, \ k., \tag{10}$$

where R_{it} is independently and identically distributed for the overall fixed i and time (t), which is orthogonal to i and t, as mentioned by Machado and Silva (2019). This helps stabilize the components and reserves of exogenous behavior. Thus, Eq. (1) could be transformed, expressed as follows:

$$Q_y(\tau R_{it}) = (\theta_i + \delta_i q(\tau)) + \vartheta R_{it} + \rho \acute{Z}_{it} q(\tau). \tag{11}$$

where Eq. (11) illustrates that R_{it} is a vector collectively represents all explanatory variables collectively, including *GDP*, *REC*, *R&D*, *and PPIE*, where these variables are taken in the natural log. While R_{it} is quantile distribution for Y_{it}, indicating *ERGHG*, is conditional on explanatory variables' location. Moreover, $-\theta_i(\tau) \equiv \theta_i + \delta_i \ q(\tau)$, is the scalar coefficient indicating fixed effect of τ quantiles for i. Individual impact, on the other hand, does not affect the intercept. Because the variables are not time-dependent, the various effects are likely to change. Finally, $q(\tau)$ demonstrates the $\tau - th$ sample quantiles, which is assumed four in current study: specifically, 25th, 50th, 75th, and 90th quantile. Hence, this research utilized the following equation for quantile:

$$min_q \sum_i \sum_t \gamma_\tau \left(R_{it} - (\delta_i + \rho \acute{Z}_{it}) q \right). \tag{12}$$

where $\gamma_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$, describes the check function.

3.1.6. Panel Causality Test

The MMQREG method gives estimated outputs for each regressor at a given scale and location, but this does not convey details about the causal link between regressors and dependent variables. To assess causal connection among these factors, this research used Dumitrescu and Hurlin (2012) Granger panel causality heterogeneity test. When dealing with an imbalanced panel ($T \neq N$), this test is more effective and stronger. It also resolves panel data heterogeneity and cross-sectional dependency (Banday & Aneja, 2020).

4. Results and Discussion

This section deals with the results estimation and their interpretation via following the estimation techniques discussed in the earlier section. Initially, this study

Table 1. Descriptive and normality statistics.

	ERGHG	*GDP*	*REC*	*R&D*	*PPIE*
Mean	1.303864	12.05257	1.252865	−0.026512	9.025784
Median	1.180189	12.07424	1.269185	−0.007557	9.089045
Maximum	1.911002	13.16530	1.768289	0.330531	10.47319
Minimum	0.579824	11.25372	0.502495	−0.249307	6.477121
Std. Dev.	0.430707	0.444692	0.424721	0.135124	0.811741
Skewness	−0.095173	0.333971	−0.570124	0.764890	−1.086351
Kurtosis	1.880284	3.105873	1.960703	3.363596	4.315660
Jarque-Bera	8.331214	2.953752	15.37280	15.96777	41.66654
Probability	0.015520	0.228350	0.000459	0.000341	0.000000

Source: authors own estimated.

calculates the descriptive statistics and estimates for normality of the variables as provided in Table 1. Specifically, the mean and median values for *ERGHG*, *GDP*, *REC*, *and PPIE*. This shows that all the variables are following an increasing trend. However, the only variable that portrays negative mean and median values is *R&D*, indicating the diminishing trend. Besides, the maximum and minimum values are also given that covers the selected period from 1990 to 2020. In this regard, the value of *PPIE* is noted with the highest difference, i.e., the value ranges from a minimum of 6.477 and reaches to the maximum of 10.473, followed by *GDP*, *ERGHG*, *REC*, and *R&D*. The difference between the minimum and maximum values indicates the fluctuating or inconsistent trends of the variables, which could also be detected via standard deviation. That is, the standard deviation of *PPIE* (0.8117) is noted as the highest, indicating the highest volatile variable from the selected model, followed by *GDP* (0.4446), *ERGHG* (0.4307), *REC* (0.4247), and *R&D* (0.1351). Moreover, the skewness and Kurtosis of all the variables are found displaced relative to the proposed values of these estimators. However, the Jarque and Bera (1987) normality test: which considers skewness and excess Kurtosis equal to zero as a null hypothesis, reveals that the probability values for all the variables except *GDP* are found statistically significant at 1% levels. Thus, it is concluded that *ERGHG*, *REC*, *R&D*, *and PPIE* are not normally distributed. Following the non-normal distribution of data, it is important to utilize an appropriate panel data estimating approach that allows for irregularity issues of data.

This study examines the slope coefficient heterogeneity and cross-sectional dependence, which are existing panel data issues and important to analyse before identifying the specific association that exists between the variables. Table 2 demonstrates the estimated values for slope heterogeneity. Here, it is found that both the $\hat{\Delta}_{SCH}$ and $\hat{\Delta}_{SCH}$ Values are highly statistically significant at 1% level. Therefore, the null hypothesis of Pesaran and Yamagata (2008) SCH test may be rejected to conclude that the slope coefficients are heterogeneous. In addition, Table 3 provides estimated results of cross-sectional dependency of the panel. The examined results report that the values of *ERGHG*, *GDP*, *REC*, *R&D*, and *PPIE* are highly statistically significant to reject the null hypothesis of Pesaran (2021) PCD test. Thus, it is concluded that all the variables are cross-sectionally dependent throughout the panel. As mentioned earlier, a country specializing in a particular commodity and services encourages the dependency of other countries or regions on that particular economy. Due to this dependency, these dependent economies may show resemblance in some respects and

Table 2. Slope heterogeneity.

Slope Heterogeneity Test	Statistics
$\sim\Delta$	8.348***
$\sim\Delta^{Adjusted}$	9.296***

*Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.*
Source: authors own estimated.

Table 3. Cross-section dependence.

Cross-Section Dependence	
ERGHG	*GDP*
−2.327**	16.066***
REC	*R&D*
10.31***	6.03***
PPIE	
1.492***	

*Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.*
Source: authors own estimated.

Table 4. Unit root testing (Pesaran, 2007).

	Intercept and Trend	
Variables	I(0)	I(1)
ERGHG	−0.878	−3.547***
GDP	−1.625	−3.052**
REC	−2.443	−4.380***
R&D	−2.540	−5.304***
PPIE	−3.611***	–

*Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%. I(0) is for level, and I(1) is for the first.*
Source: authors own estimated.

differences in other aspects. However, in case of the BRICS economies, the slope coefficients are heterogeneous; still, the variables under consideration are cross-sectionally dependent. Therefore, this study utilizes an appropriate estimator that allows for both the panel data concerns.

Since the earlier tests confirm that the slope coefficients are heterogeneous and the cross-section dependence is present in the variables. Therefore, this study adopted the second-generation unit root test to tackle SCH and PCD (Pesaran, 2007). The estimated results of this test are provided in Table 4. From the results, it is observed that four variables, including *ERGHG*, *GDP*, *REC*, and *R&D* have a unit root at I(0). However, the only variable found stationary at I(0) is *PPIE*. On the other hand, the I(0) non-stationary variables became stationary at I(1). Specifically, the estimates of *ERGHG*, *GDP*, *REC*, and *R&D* provides statistically significant estimates at 1% and 5% levels to reject the null hypothesis of unit root presence in the variables. Instead, all the variables are stationary—which allows current study to analyse the co-integration relationship between the variables.

Although the variables under discussion follow mixed order of integration, ye all variables are stationary at I(0) or I(1). Therefore, this study investigated the long-run equilibrium relationship between the variables. In this sense, the Westerlund (2007) ECM test is employed, where the obtained results are presented in Table 5. As stated above, this test assumes the error correction term equals zero. However, the result

Table 5. Co-integration results (Westerlund-2007).

Statistics	Value	Z-value
G_τ	−4.114***	−4.643
G_a	−24.583***	−4.623
P_τ	−14.419***	−8.528
P_a	−52.537***	−14.198

*Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.*
Source: authors own estimated.

Table 6. Estimates of quantile regression–MMQR.

			Quantiles			
Variable	Location	Scale	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
GDP	0.643***	−0.009	0.653***	0.642***	0.634***	0.630***
	[0.048]	[0.022]	[0.057]	[0.048]	[0.049]	[0.052]
REC	−0.968***	0.074***	−1.047***	−0.962***	−0.893***	−0.863***
	[0.036]	[0.016]	[0.043]	[0.038]	[0.037]	[0.032]
R&D	−1.600***	0.024	−1.626***	−1.598***	−1.575***	−1.565***
	[0.169]	[0.077]	[0.200]	[0.168]	[0.173]	[0.183]
PPIE	−0.076***	−0.002	−0.073***	−0.076***	−0.079***	−0.080***
	[0.018]	[0.008]	[0.022]	[0.019]	[0.019]	[0.020]
Constant	−4.591***	0.198	−4.801***	−4.575***	−4.392***	−4.312***
	[0.564]	[0.258]	[0.671]	[0.564]	[0.579]	[0.615]

*Note: ERGHG is dependent variable. Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.*
Source: authors own estimated.

revealed that both the panel (P_τ and P_a) statistics and group mean (G_τ and G_a) statistics are highly significant at 1% level. Therefore, the null hypothesis could be rejected—indicating the non-zero error correction term. Thus, the long-run equilibrium relationship is present in the variables throughout the selected period. Hence, the long-run co-integration relationship allows this study to analyse the specific influence of variables such as *GDP*, *REC*, *R&D*, *and PPIE* on *ERGHG*.

As discussed earlier, the variables are found stationary, and the long run equilibrium relationship exists between them. In this sense, current study utilizes the novel MMQREG specifications to examine the specific impact of each explanatory variable on *ERGHG*. The estimated results are given in Table 6. From the examined results, the particular location and scale are presented along with the specific influence of variables at four considered quantiles, i.e., $Q_{0.25}$, $Q_{0.50}$, $Q_{0.75}$, and $Q_{0.90}$. The results indicate that economic growth captured by *GDP* is the only significant factor that enhances the pollution level in the BRICS economies. To be more specific, a one percent increase in the *GDP* enhances the *ERGHG* emissions by $0.653 - 0.630\%$, which follows a decreasing trend while moving from lower ($Q_{0.25}$) to the middle ($Q_{0.50}$–$Q_{0.75}$) and to upper ($Q_{0.95}$) quantiles. The results estimated are found highly statistically significant at 1% level and are consistent to the existing studies of Li and Li (2020) in case of China, and Shahbaz et al. (2020) in case of UK. The reason for positive influence of *GDP* on *ERGHG* is that with the increase of economic growth or income level, the domestic as well as commercial level energy consumption increases. Besides, the production of goods and services also increases along with the industrial sector expansion. This increase in the said sectors uses more energy obtained from fossil fuel or other non-renewable energy sources. However, the combustion of such non-renewable energy resources boosts the emissions level in the BRICS economies, further causing environmental degradation and global warming.

On the other hand, *REC*, *R&D*, *and PPIE* are noted as negatively associated with *ERGHG* emissions. An increase of one percent in the *REC*, *R&D*, *and PPIE* significantly reduces *ERGHG* by 1.047 – 0.863%, 1.626 – 1.565%, and 0.073 – 0.080% across the quantiles, respectively. These results are found statistically significant at 10%, 5%, and 1% at all the quantiles. Enhancement in the level of renewable energy consumption reduces fossil fuel consumption, which help reduce emissions level. Besides, the increased income level tends to promote renewable energy by replacing the traditional non-renewable energy technologies. Hence, the more the use of renewable energy, the less will reduce fossil fuel energy consumption as the energy demand is fulfilled via renewables at both the household level and industrial level. Therefore, the increased consumption of renewable energy reduces environmental degradation by declining the level of *ERGHG* emissions. The current findings regarding the negative association of *REC* and *ERGHG* is consistent (Dincer, 2000, Baskutis et al., 2021; Yongjun et al., 2021). In addition, the enhanced level of research and development expenditures promote the culture of environmentally friendly and advanced technologies that consider energy use in efficient manners to reduce the use of traditional fossil fuel energy. Due to this, renewables and other environmentally friendly resources help fulfil energy demand without disturbing environmental quality. Consequently, the *ERGHG* emissions level tends to reduce. This study's estimated results are in line with the empirical findings of Khan et al. (2021) in the global sample of 219 countries and Wan et al. (2022) in the case of 217 economies. Moreover, the magnitude of the influence is found to decrease for both *REC*, and *R&D* while moving from lower to upper quantile(s). On the other hand, the magnitude of influence for *PPIE* is found increasing from lower to upper quantiles. The results demonstrate that the public–-private partnerships investment in the BRICS economies are more diverted to renewable energy and technological innovation. The use of non-renewable energy and energy intensive products and services reduces. Thus, the enhanced level of *PPIE* tends to reduce *ERGHG* in the BRICS region. Similar results are also provided by Raza et al. (2021) in developing economies, and Kirikkaleli and Adebayo (2021) in India.

As earlier mentioned, the MMQREG specifications are limited to revealing the causal nexus between the variables under consideration. Therefore, this study employs Dumitrescu and Hurlin (2012) Granger panel causality heterogeneity test, where the results are displayed in Table 7. The estimated results unveil a two-way causal association between *ERGHG* and *GDP*, *ERGHG* and *REC*, *ERGHG* and *R&D*. This indicates that any policy level changes in either explanatory variable could influence the policies related to *ERGHG*, while the feedback hypothesis is also present. These results are consistent with the existing studies of Saidi and Omri (2020). However, there is a unidirectional causal influence reported from *PPIE* to *ERGHG*, while no feedback effect is observed in this causal association. This demonstrates that *PPIE*, *GDP*, *REC*, and *R&D* could be effective policy tools for environmental recovery or controlling *ERGHG* emissions in the BRICS economies.

Table 7. Dumitrescu-Hurlin panel causality.

H_0	$Wald_{Stats}$	$\bar{Z}_{stats}$	p − value
GDP ⇏ *ERGHG*	12.5216***	15.7547	0.0000
ERGHG ⇏ *GDP*	22.3760***	29.3239	0.0000
REC⇏ *ERGHG*	3.59497***	3.46303	0.0005
ERGHG⇏ *REC*	9.18566***	11.1612	0.0000
R&D ⇏ *ERGHG*	2.98623***	2.62482	0.0087
ERGHG ⇏ R&D	5.93223***	6.68136	2.E-11
PPIE ⇏ *ERGHG*	4.20241***	3.54553	0.0000
ERGHG ⇏ *PPIE*	2.07587	1.37128	0.1703

Note: Significance level is denoted by *** *for 1%,* ** *for 5% and* * *for 10%.*
Source: authors own estimated.

5. Conclusion and Policy Implications

The major issue of the current time is environmental recovery or emissions control. Although, both the developed and developing economies are in the same war of environmental recovery, however, the emerging economies are more at risk in this battle due to two major challenges. Specifically, the developing economies are struggling for economic sustainability and the pressure of environmental recovery. Therefore, this study aims to examine whether renewable energy could be a path for emerging economies like BRICS, to tackle energy related greenhouse gas emissions during the period 1990–2020. Also, these countries also focused on other factors like economic growth, research and development, and public–private partnership investment in energy, which could influence energy related greenhouse gas emissions. This study used various panel data instruments such as slope heterogeneity, panel cross-section dependence, and second-generation unit root test. The variables under consideration are found co-integrated, where the non-normal distribution of data forces this study to use novel MMQREG specifications to tackle the said issue. The estimated results reveal that economic growth is a primary factor that enhances the emissions level in the BRICS economies. Specifically, the increased income level encourages investors and industrialists to invest in and expand the industrial sector, which needs more fuel for enhanced production. However, this need for energy or fuel is fulfilled via non-renewable energy resources. Therefore, economic growth is favouring environmental degradation via increasing the energy related emissions level in the region. On the other hand, investment in R&D and enhancement in the public–private partnership investment in energy reduce the emissions level. Such that R&D investment and the latter are more diverted to the encouragement of renewable energy in the BRICS economies, which are found favorable for environmental sustainability and controlling energy related emissions. Besides, the causal associations asserted that economic growth, renewable energy consumption, R&D, and public–private partnership investment in energy could be used as policy measures to reduce energy related emissions in the region.

Based on the empirical results, this study suggests some policies that could help BRICS economies tackle energy-related emissions. First, the increased level of income is noted to affect environment adversely. Therefore, policies are required to transform industrial structure from fossil fuel energy to renewable energy, energy efficient, and environmentally friendly technologies via efficient utilization of economic growth.

This will help reduce energy related emissions in the region. Secondly, renewable energy consumption must be considered an important policy factor for reducing environmental hazards. Thus, promoting renewable energy could help lower fossil fuel energy use and consequently lead to environmental sustainability. Thirdly, research and development should be highly considered for environmental quality sustainability. It promotes the culture of energy efficiency, renewable energy, sustainable use of natural resources, and technologically advanced equipment in the industrial sector. Therefore, this could be a prominent tool for reducing energy related emissions. Lastly, the public–private partnership investment should increase in the field of renewable energy instead of fossil fuel energy. This will fuel the production and use of renewable energy, a prominent source of emissions reduction.

Disclosure statement

The authors declare no conflict of interest.

Note

1. For data and Information, visit: https://databank.worldbank.org/source/world-development-indicators

Funding

This work was supported by Liaoning Social Science Federation Project 'Research on Accelerating the Construction of Collaborative Innovation System of Data Center in Liaoning Province' (2022lslwtkt-038).

References

Assi, A. F., Isiksal, A. Z., & Tursoy, T. (2021). Renewable energy consumption, financial development, environmental pollution, and innovations in the ASEAN+ 3 group: Evidence from (P-ARDL) model. *Renewable Energy*, *165*, 689–700. https://doi.org/10.1016/j.renene.2020.11.052

Banday, U. J., & Aneja, R. (2020). Renewable and non-renewable energy consumption, economic growth and carbon emission in BRICS: Evidence from bootstrap panel causality. *International Journal of Energy Sector Management*, *14*(1), 248–260. https://doi.org/10.1108/IJESM-02-2019-0007

Baskutis, S., Baskutiene, J., Navickas, V., Bilan, Y., & Cieśliński, W. (2021). Perspectives and problems of using renewable energy sources and implementation of local "Green" initiatives: A regional assessment. *Energies*, *14*(18), 5888. https://doi.org/10.3390/en14185888

Borba, B. S., Lucena, A. F., Rathmann, R., Costa, I. V., Nogueira, L. P., Rochedo, P. R., Branco, D. A. C., Júnior, M. F., Szklo, A., & Schaeffer, R. (2012). Energy-related climate change mitigation in Brazil: Potential, abatement costs and associated policies. *Energy Policy*, *49*, 430–441. https://doi.org/10.1016/j.enpol.2012.06.040

BP. (2020). Statistical review of world energy. http://www.bp.com/statisticalreview

Breitung, J. (2005). A parametric approach to the estimation of cointegration vectors in panel data. *Econometric Reviews*, *24*(2), 151–173. https://doi.org/10.1081/ETC-200067895

Brundtland, G. H., & Khalid, M. (1987). *The Brundtland report: 'Our common future', medicine and war* (pp. 17–25), 4(1). Oxford University Press.

Campello, M., Galvao, A. F., & Juhl, T. (2019). Testing for slope heterogeneity bias in panel data models. *Journal of Business & Economic Statistics*, *37*(4), 749–760. https://doi.org/10.1080/07350015.2017.1421545

Charabi, Y. (2021). Digging deeper into cutting methane emissions from the oil and gas industry in the era of volatile prices. *Mitigation and Adaptation Strategies for Global Change*, *26*(2), 1–15. https://doi.org/10.1007/s11027-021-09948-3

Cheng, G., Zhao, C., Iqbal, N., Gülmez, Ö., Işik, H., & Kirikkaleli, D. (2021). Does energy productivity and public-private investment in energy achieve carbon neutrality target of China? *Journal of Environmental management*, *298*, 113464. https://doi.org/10.1016/j.jenvman.2021.113464

Climate action network. (2021). https://caneurope.org/methane-emissions-energy-sector-effective-action-tackle-invisible-menace/

Dincer, I. (2000). Renewable energy and sustainable development: A crucial review. *Renewable and Sustainable Energy Reviews*, *4*(2), 157–175. https://doi.org/10.1016/S1364-0321(99)00011-8

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, *29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

El-Fadel, M., Chedid, R., Zeinati, M., & Hmaidan, W. (2003). Mitigating energy-related GHG emissions through renewable energy. *Renewable Energy*, *28*(8), 1257–1276. https://doi.org/10.1016/S0960-1481(02)00229-X

Frank, E. D., Han, J., Palou-Rivera, I., Elgowainy, A., & Wang, M. Q. (2012). Methane and nitrous oxide emissions affect the life-cycle analysis of algal biofuels. *Environmental Research Letters*, *7*(1), 14030. https://doi.org/10.1088/1748-9326/7/1/014030

Global Methane Initiative. (2004). https://www.epa.gov/gmi/learn-about-global-methane-initiative

Gyamfi, S., Derkyi, N. S., Asuamah, E. Y., & Aduako, I. J. (2018). Renewable energy and sustainable development. In *Sustainable hydropower in West Africa*. (pp. 75–94). Academic Press.

Hashimoto, K., Kumagai, N., Izumiya, K., Takano, H., & Kato, Z. (2014). The production of renewable energy in the form of methane using electrolytic hydrogen generation. *Energy, Sustainability and Society*, *4*(1), 1–9. https://doi.org/10.1186/s13705-014-0017-5

Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review/Revue Internationale de Statistique*, *55*(2), 163–172. https://doi.org/10.2307/1403192

Khan, M. K., Trinh, H. H., Khan, I. U., & Ullah, S. (2021). Sustainable economic activities, climate change, and carbon risk: An international evidence. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-021-01842-x

Kirikkaleli, D., & Adebayo, T. S. (2021). Do public-private partnerships in energy and renewable energy consumption matter for consumption-based carbon dioxide emissions in India? *Environmental Science and Pollution Research International*, *28*(23), 30139–30152. https://doi.org/10.1007/s11356-021-12692-5

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica*, *46*(1), 33–50. https://doi.org/10.2307/1913643

Le, H. P., & Bao, H. H. G. (2020). Renewable and nonrenewable energy consumption, government expenditure, institution quality, financial development, trade openness, and sustainable development in Latin America and Caribbean emerging market and developing economies. *International Journal of Energy Economics and Policy*, *10*(1), 242–248. https://doi.org/10.32479/ijeep.8506

Li, J., & Li, S. (2020). Energy investment, economic growth and carbon emissions in China—Empirical analysis based on spatial Durbin model. *Energy Policy*, *140*, 111425. https://doi.org/10.1016/j.enpol.2020.111425

Machado, J. A., & Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics*, *213*(1), 145–173. https://doi.org/10.1016/j.jeconom.2019.04.009

Mardani, A., Streimikiene, D., Cavallaro, F., Loganathan, N., & Khoshnoudi, M. (2019). Carbon dioxide (CO2) emissions and economic growth: A systematic review of two decades of research from 1995 to 2017. *The Science of the Total environment*, *649*, 31–49. https://doi.org/10.1016/j.scitotenv.2018.08.229

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, *60*(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, *74*(4), 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of applied econometrics*, *22*(2), 265–312.

Petrović, P., & Lobanov, M. M. (2020). The impact of R&D expenditures on CO2 emissions: Evidence from sixteen OECD countries. *Journal of Cleaner Production*, *248*, 119187. https://doi.org/10.1016/j.jclepro.2019.119187

Radmehr, R., Henneberry, S. R., & Shayanmehr, S. (2021). Renewable energy consumption, CO2 emissions, and economic growth nexus: A simultaneity spatial modeling analysis of EU countries. *Structural Change and Economic Dynamics*, *57*, 13–27. https://doi.org/10.1016/j.strueco.2021.01.006

Raza, S. A., Shah, S. H., & Yousufi, S. Q. (2021). The impact of public-private partnerships investment in energy on carbon emissions: Evidence from nonparametric causality-in-quantiles. *Environmental Science and Pollution Research international*, *28*(18), 23182–23192. https://doi.org/10.1007/s11356-020-12306-6

Rehman, A., Ma, H., Irfan, M., & Ahmad, M. (2020). Does carbon dioxide, methane, nitrous oxide, and GHG emissions influence the agriculture? Evidence from China. *Environmental Science and Pollution Research international*, *27*(23), 28768–28779. https://doi.org/10.1007/s11356-020-08912-z

Reisinger, A., Clark, H., Cowie, A. L., Emmet-Booth, J., Gonzalez Fischer, C., Herrero, M., Howden, M., & Leahy, S. (2021). How necessary and feasible are reductions of methane emissions from livestock to support stringent temperature goals? *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2210), 20200452. https://doi.org/10.1098/rsta.2020.0452

Saidi, K., & Omri, A. (2020). The impact of renewable energy on carbon emissions and economic growth in 15 major renewable energy-consuming countries. *Environmental research*, *186*, 109567. https://doi.org/10.1016/j.envres.2020.109567

Sarkodie, S. A., & Strezov, V. (2019). A review on environmental Kuznets curve hypothesis using bibliometric and meta-analysis. *The Science of the Total environment*, *649*, 128–145. https://doi.org/10.1016/j.scitotenv.2018.08.276

Shahbaz, M., Zakaria, M., Shahzad, S. J. H., & Mahalik, M. K. (2018). The energy consumption and economic growth nexus in top ten energy consuming countries: Fresh evidence from using the quantile-on-quantile approach. *Energy Economics*, *71*, 282–301. https://doi.org/10.1016/j.eneco.2018.02.023

Shahbaz, M., Nasir, M. A., Hille, E., & Mahalik, M. K. (2020). UK's net-zero carbon emissions target: Investigating the potential role of economic growth, financial development, and R&D expenditures based on historical data (1870–2017). *Technological Forecasting and Social Change*, *161*, 120255. https://doi.org/10.1016/j.techfore.2020.120255

Tarazkar, M. H., Kargar Dehbidi, N., Ansari, R. A., & Pourghasemi, H. R. (2021). Factors affecting methane emissions in OPEC member countries: Does the agricultural production matter? *Environment, Development and Sustainability*, *23*(5), 6734–6748. https://doi.org/10.1007/s10668-020-00887-8

Wan, G., Wang, C., Wang, J., & Zhang, X. (2022). The income inequality-CO2 emissions nexus: Transmission mechanisms. *Ecological Economics*, *195*, 107360. https://doi.org/10.1016/j.ecolecon.2022.107360

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, *69*(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

WMO. (2019). World Meteorological Organization, WMO statement on the state of the global climate in 2018. https://library.wmo.int/doc_num.php?explnum_id=5789.

World Bank. (2018). The World Bank Annual Report 2018. http://documents.worldbank.org/curated/en/630671538158537244/The-World-Bank-Annual-Report-2018

Yilanci, V., & Pata, U. K. (2020). Convergence of per capita ecological footprint among the ASEAN-5 countries: Evidence from a non-linear panel unit root test. *Ecological Indicators*, *113*, 106178. https://doi.org/10.1016/j.ecolind.2020.106178

Yongjun, G., Liu, J. L., & Bashir, S. (2021). Electrocatalysts for direct methanol fuel cells to demonstrate China's renewable energy renewable portfolio standards within the framework of the 13th five-year plan. *Catalysis Today*, *374*, 135–153. https://doi.org/10.1016/j.cattod.2020.10.004

Yusaf, T., Goh, S., & Borserio, J. A. (2011). Potential of renewable energy alternatives in Australia. *Renewable and Sustainable Energy Reviews*, *15*(5), 2214–2221. https://doi.org/10.1016/j.rser.2011.01.018

Zhang, B., Chen, G. Q., Li, J. S., & Tao, L. (2014). Methane emissions of energy activities in China 1980–2007. *Renewable and Sustainable Energy Reviews*, *29*, 11–21. https://doi.org/10.1016/j.rser.2013.08.060

Zhang, B., Zhang, Y., Wu, X., Guan, C., & Qiao, H. (2020). How the manufacturing economy impacts China's energy-related GHG emissions: Insights from structural path analysis. *The Science of the Total environment*, *743*, 140769. https://doi.org/10.1016/j.scitotenv.2020.140769