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Novel research methods to evaluate renewable energy and energy-related greenhouse gases: evidence from BRICS economies

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ABSTRACT

This study examined renewable energy, energy efficiency which is very essential to boost up environmental quality. This research also takes other factors which has impact on greenhouse gas emissions in the BRICS nations between 2000 and 2019. On the other hand, this research differs from previous research in that it considers the impact of Energy Efficiency and Renewable Energy Electricity on greenhouse gas emissions in BRICS economies, despite the fact that Energy Efficiency and Renewable Energy Electricity have the greatest impact on greenhouse gas emissions in BRICS economies. The influence of GDP and political risk index on energy-related greenhouse gas emissions also comes under the scope of this study. Further, the order of unit root was determined using cross-sectional dependency and slope heterogeneity. The results were achieved utilising moment quantile regression (MMQ). The analysis shows that GDP causes an increase in Energy-Related Greenhouse Gases (ERGHG) at the 25th, 50th, 75th and 90th quantiles. At the 25th, 50th, 75th and 90th quantiles, however, Energy Efficiency and Renewable Energy Electricity reduce Energy-Related Greenhouse Gases. Furthermore, political risk index reduces Energy-Related Greenhouse Gas emissions. Moreover, policymakers should investigate the asymmetric behaviour of Energy Efficiency, Electricity from Renewable Energy and GDP when adopting BRICS economies energy, environment and growth policies based on empirical data.

Nomenclature: Energy Efficiency; ENEF: Energy-Related Greenhouse Gases; ERGHG: Political Risk Index; PRI: South Africa, Russia, India, Brazil, China; BRICS: Electricity from Renewable; ELRE: Gross Domestic Product; GDP: Mean Group; MG: Method of Moments Quantile Regression; MMQR:

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1. Introduction

Over the last few years, anthropogenic Greenhouse Gas (GHG) emissions have continuously grown. As per the United Nations, global total GHG emissions have touched a new high level of 53 Gt CO₂ closest approximation around the second half of 2017 (United Nations Environment Programme (UNEP), 2018). This is more than double what it was in the year 1970. CO₂ is the most prevalent GHG, and it has long been considered that emissions from fossil fuel burning are the most important factor in influencing atmospheric carbon levels. The second most major GHG is methane (CH₄), mostly produced by energy and agricultural activities (Montzka et al., 2011). China reported nearly a quarter of worldwide overall emissions in 2017, as the world's major emitter of GHG. The majority of its emissions come from the energy sector (BP, 2018). Additionally, fuel-burning accounted for 89.5 per cent of CO₂ emissions in 2014, whereas energy activities accounted for 48.0 per cent of CH₄ emissions (World Bank, 2019). As a consequence of industrialisation and growing energy consumption, China's GHG emissions are predicted to continue to climb in the coming years. It is necessary to take strong actions to cut energy-related GHG emissions and bring carbon emissions to a standstill by 2030. The most important consideration in setting environmental goals is to maintain the developing world's EG. The BRICS economies, in particular, are projected as a driving influence in the EG (Shao et al., 2019). The GDP of the BRICS economies increased by 6.5 per cent annually from US\$1626 billion in 2016 to US\$2187 billion in 2018 (World Bank, 2018). Despite this, the BRICS economies' rise has resulted in a number of environmental issues, notably more CO₂ emissions. CO₂ emissions in the BRICS economies increased thrice between 1985 and 2018, from 4901 Mt to 13,768 Mt (World Bank, 2018). The BRICS economies have contributed significantly to global economic progress, but they have also contributed to global GHG emissions. China, for example, is the world's second-largest economy, accounting for more than 20% of global GDP, yet it pollutes the environment, producing more than 40% of global CO₂ emissions in 2016 (Dong et al., 2017). These findings have major implications for reducing greenhouse gas emissions and air pollution (Reilly, 2015). As major and emerging countries, the BRICS' top aim is to work together to meet global carbon-reduction targets (Liu et al., 2017). The BRICS economies should prioritise Energy Efficiency (EE) and Renewable Energy (RE) supplies, as well as solutions for reducing emissions without jeopardising EG (de Castro Camioto et al., 2016). As a result, RE & ENEF initiatives are crucial for the BRICS economies in reducing GHG emissions and mitigating climate change.

The ENEF is an essential policy instrument for decreasing environmental harm and isolating the ecosystem from GHG emissions. The term 'energy efficiency factor' refers to the use of less energy to create the same quantity of output (Özcan & Özkan, 2018). Rising ENEF investment has a number of advantages. For example, ENEF projects can improve ecosystem resilience, decrease environmental burdens by reducing emissions, ease reliance on FFs, enhance energy security, mitigate power outages, and boost competition in the industrial sector by cutting expenditures (European Commission, 2016). ENEF is also a key component of the BRICS economies' green development programs, aiming to cut CO₂ emissions by improving EE

(Bayar & Gavriletea, 2019). Additionally, fulfilling the Sustainable Development Goals (SDGs) needs the increased usage of ENEF (Shahbaz et al., 2019). As a result, ENEF is a critical issue for the BRICS economies to sustain rapid industrialisation, close the energy deficit gap, and limit the consequences of GHG emissions.

In a variety of ways, the study adds to the current body of literature. To begin with, previous research has placed a greater emphasis on EE and RE sources than on carbon emissions. Instead, this article looks at the impact of EE, RE Electricity, and Energy-Related Greenhouse Gases. Second, this is the first research to look at how EE, RE Electricity, and Energy-Related Greenhouse Gases affect the BRICS countries. Third, the study provides critical information for the BRICS nations on the causative link between EE, RE electricity, and ERGHG emissions. These data will aid policy-makers in creating effective GHG emission reduction measures. Fourth, the study sheds light on the relationship between income, power generation, and pollution. Fifth, most previous research investigating environmental contamination has employed the EKC hypothesis and the STIRPAT model, ARDL, and CS-ARDL. Safi et al. (2021). The relationship between hydropower output, renewable electricity generation, and CO₂ emissions is explored using a novel method that involves the development of both a conceptual and empirical model. The following section is formatted as per, Section 2 delves deeper into prior empirical and theoretical studies. Section 3 delves into the variables and their data sources, the hypothetical framework, specification of the model, and related methodology. Section 4 examines the pragmatic findings. Section 5 concludes the report by outlining key policy suggestions based on the findings.

2. Literature

Numerous studies on different economies and regions over EE, Electricity from RE and ERGHG. In the research that was looked into, various methodologies and various regions were used for the results. Some of the literature is as under.

Akram et al. (2020) investigated EE and RE over carbon emission for BRICS countries utilising Panel data analysis-NPARDL from 1990 till 2014 and their finding shows Asymmetric impacts (SR and LR). Furthermore, Yuan et al. (2011), Shao et al. (2014). Zhou et al. (2018), Wu et al. (2012) examined china for EE and carbon emission, all of them have the same result, and the authors find a negative relation of EE with carbon emission. Moreover, the same negative relationship of EE and carbon emission found by Özbuğday and Erbas (2015) Abban et al. (2020), Iftikhar et al. (2016), Pardo and Moya (2013) by investigating 36 DEE countries, 43 countries; part of Belt and Road Initiative and 26 major economies, respectively.

Many scholars have looked at the relationship between economic development and environmental deterioration, according to Grossman and Krueger (1991) study. Even yet, the majority of previous studies are ambiguous and debatable. Previous studies on the hypothesised linkages among energy usage and environmental degradation have also failed to agree on the causality trend. Destek (2016) utilised asymmetric causation to find the association between RE use and economic growth in recently industrialised countries for the period of 1971 to 2011. According to the statistics, the

utilisation of RE has an optimistic influence on actual GDP in South Africa and Mexico. In Turkey, Pata (2018) looked at the dynamic connection between RE, income, and CO₂ emissions. According to research, EG has a favourable effect on Carbon emission emissions. Because the effect of RE is modest, Turkey did not achieve the appropriate amount of RE required to reduce emissions. According to Azevedo et al. (2018) CO₂ emissions in Russia and Brazil (group 1) are influenced by GDP, but emissions in China, South Africa, and India (group 2) are unaffected by income levels. Increased economic activity has a mixed environmental impact as a result. Balsalobre-Lorente et al. (2019) used panel data from the BRICS economies to assess the influence of AGRs on CO₂ emissions. According to the findings, AGR operations had a detrimental impact on the environment.

Furthermore, EC and trading encouraged environmental vulnerabilities. According to Baloch et al. (2019), the presence of NRs aids in the decrease environmental pollution in BRICS economies. Furthermore, except for South Africa, the environmental impact of RE is positive. According to Cheng et al. (2019), environmental factors have varying implications based on present CO₂ emissions levels. The authors investigated how CO₂ emissions received effect from RE, environmental patent applications, and EG in BRICS nations and discovered that renewable energy reduces CO₂ emissions while EG raises them. Pao and Tsai (2011) utilised the panel cointegration approach to analyse environmental quality while changes in FDI and EG in BRIC economies. According to the report, EG is the leading reason for environmental pollution. Lin and Moubarak (2014) looked at RE use's short-run and long-term effects on pollutant emissions. According to the study, China's current level of RE is much below what is required to improve environmental quality. In Pakistan, Zhang et al. (2017) investigated the impact of renewable and nonrenewable energy (NRE) consumption on CO₂ emissions. NRE is the leading cause of environmental harm, according to the statistics, but RE helps to reduce it. Dong et al. (2017) examined the link between CO₂ emissions and RE in BRICS countries after accounting for natural gas (NG). The study found that using RE and NG increased environmental quality. According to the research, although RE and EG enhanced environmental quality in BRICS nations, NRE and AGRs degraded it.

Wahab et al. (2021) investigated energy productivity with carbon emission for G-7 economies from 1996 to 2017 using CS-ARDL, which is one of the most famous researches in this field. According to S. Wahab's research, energy production has an inverse connection with carbon emissions, just as technical innovation and export have a contrary association amid carbon emissions. Whereas, EG and trade have a favourable relationship with carbon emissions. Furthermore, Wahab et al. (2022) used a spatial Durbin model to analyse RE and financial stability in relation to carbon emissions for BRICS nations from 1995 to 2018. According to S. Wahab's results, RE has counter connection to carbon emissions, and export has an opposite connection with carbon emissions as well. Carbon emissions have a positive relationship with GDP and imports. Furthermore, Ang (2007) examined the vigorous causality between EG, EC, and pollutions using French data between 1960 and 2000 using cointegration approach and ECM. The researcher discovers a long-term association between these three factors. EC and economic development also have a short-run unidirectional

causal analysis. Ang uses the DOLS approach to study the dynamic connection in China. According to his research, energy efficiency and trade openness cut carbon emissions. carbon emissions elasticity in association with EC is anticipated to be 1.101–1.175 per cent, whereas CO₂ emissions elasticity in relation to trade openness is expected to be 0.144–0.160 per cent.

Moreover, between 1995 and 2008, Robaina-Alves and Moutinho (2014) investigate the decomposition of energy-related GHG emissions in European countries' agriculture. Their findings show that when labour productivity grows (LVA falls), emissions intensity rises as well. The EKC theory, which depicts the relationship between environment and development, is commonly used to investigate the association between economic growth and GHG emissions at the sectoral and regional levels, always in conjunction with panel data and regression analysis (Chang, 2015; Li et al., 2016; Riti et al., 2017). The EKC model is commonly used to explore the impact of different variables on GHG emissions. Decomposition methods may be used to break down changes in energy-related GHG emissions into components, with LMDI being the most desired and commonly used (Wang et al., 2017). Energy intensity, energy mix, and industry structure are proven to be the most important influencing factors. The structure of the GDP, the GDP itself, and so on (Jiang et al., 2017; Zhang et al., 2016). The IPAT has been used in certain research to examine driving variables (Shuai et al., 2017; Wang et al., 2016) and anticipate future GHG emissions (Shuai et al., 2017; Wang et al., 2016; Xu et al., 2017; Yuan et al., 2014; Yue et al., 2013). The list has been updated to incorporate population density, technology, and urbanisation.

The research enhances the current scope of literature in many ways. For example, a previous study by Akram et al. (2020), Hassan et al. (2022b), Wahab's et al. (2022) and Wahab (2021) Yuan et al. (2011), Shao et al. (2014), Wahab et al. (2021) Hassan et al. (2022a) mostly focused on EE and RE rather than carbon emissions. Wu et al. (2012), Özbuğday and Erbas (2015), Zhou et al. (2018), Iftikhar et al. (2016) and Abban et al. (2020). Instead, the influence of EE, RE Electricity, and ERGHG is examined in this article. Second, this is the first research to look at how EE, RE Electricity, and ERGHG affect the BRICS countries. Third, the report provides crucial information on the causal link between EE, RE Electricity, and ERGHG the BRICS countries. This data can assist policymakers in identifying successful approaches for reducing GHG emissions. Fourth, the EKC theory was applied in the majority of previous investigations (Khan et al., 2019; Liddle, 2017; Rahman et al., 2019; Rahman & Ahmad, 2019; Zhang & Cheng, 2009) and the STIRPAT model (Koçak & Ulucak, 2019; Liddle, 2011, 2013a, 2015; Liddle & Lung, 2010). The rest of the research is organised in the following manner. This work takes an innovative method to investigate the link between EE, RE Electricity, and ERGHG by constructing a theoretical and empirical model.

3. Methodology

3.1. Data sources and theoretical framework

The influence of ERGHG in the presence of EE and RE Electricity is investigated in this study. This study takes a unique approach in that it uses ERGHG and RE Electricity as novel exogenous variables. To obtain the results, this study also employs

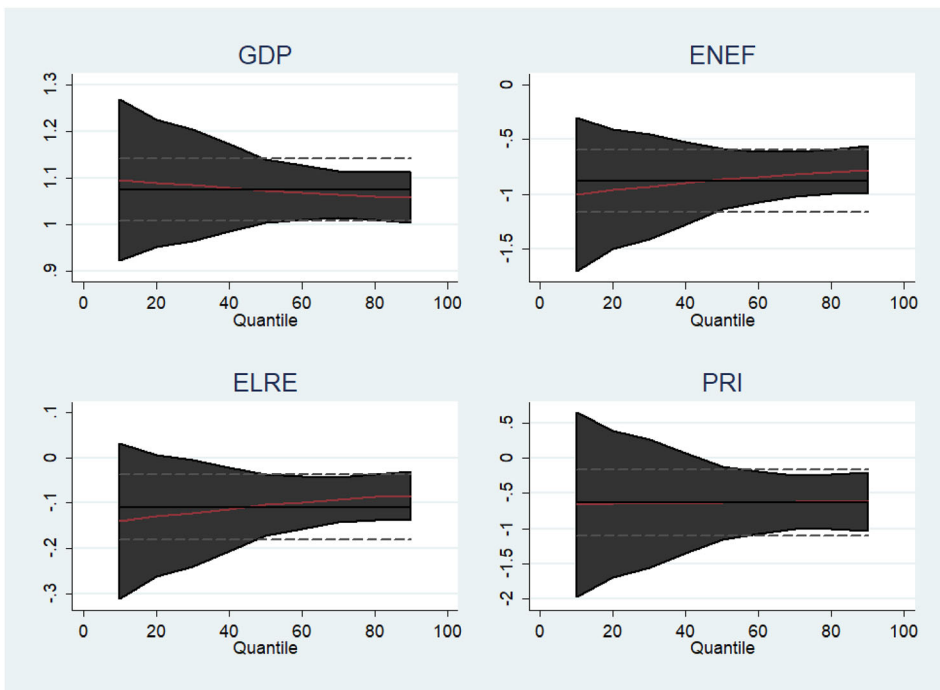


Figure 1. MMQR graph.

Source: Author's own calculations.

one of the recently established econometric methodologies. Furthermore, the preferred region as a sample for this is the list of BRICS countries, denoted by I from 2000 to 2019, denoted by t . The current data are taken for BRICS countries.¹ The present study considered the time period from 2000 to 2019, because of the availability of most recent data for all countries. All the data sets are taken from different web pages for chosen variables. This paper measured our dependent variable ERGHG from OECD² denoted by 'ERGHG'. GDP data are collected from World Bank in US dollars, 2015 and denoted by GDP. EE data is collected from World Bank GDP per unit of energy use (PPP \$per kg of oil equivalent) and is denoted ENEF. Production of electricity from sources such as renewable, excluding hydroelectric (% of total) data, is also collected from World Bank and is denoted by ELRE. While Political Risk Index data is collected from PRS data and denoted by PRI.³ Moreover, for boosting GDP a country starts investments for production to generate more income, during production, they consume more energy and fossils fuel which leads to carbon emissions. Energy-related greenhouse gases are often measured in a region's carbon emission equivalent. In Figure 1, you can see GDP has a positive relation with ERGHG while ENEF, ELRE and political risk index have a negative relation with ERGHG. The following is the model description:

$$ERGHG_{i,t} = f(GDP_{i,t}, ENEF_{i,t}, ELRE_{i,t}, PRI_{i,t}) \quad (1)$$

The essential econometric equation for this study is given by:

$$ERGHG_{i,t} = \vartheta_0 + \vartheta_1 GDP_{i,t} + \vartheta_2 ENEF_{i,t} + \vartheta_3 ELRE_{i,t} + \vartheta_4 PRI_{i,t} + \epsilon_{i,t} \quad (2)$$

The justification for adopting the variables listed in Equation (2) is based mostly on current and previous literature with a strong theoretical motivation. To boost a country's GDP, they start investing for production to generate more income; during production, they consume more energy and fossils fuel, which leads to carbon emissions. ERGHG are often measured in a region's carbon emission equivalent. When the economy of developing nations grows, the GHG emissions in the economy rise as an outcome of economic activity in the form of a large number of firms that emit GHG emisisions it is expected to have positive relation of GDP with ERGHG as you can see in Figure 1 $\vartheta_1 = \frac{\partial ERGHG_{i,t}}{\partial GDP_{i,t}} > 0$, All sources of power generation have an influence on our air, water, and land, but the extent of that impact varies. Producing and utilising energy more effectively minimises the quantity of fuel used to create power, as well as the amount of greenhouse gases and other air pollutants generated. Energy efficiency has a variety of environmental advantages. It cuts GHG emissions significantly, both directly from fossil fuel burning or consumption and indirectly through power generation. it is expected to have negative relation of ENEF with ERGHG as you can see in Figure 1 $\vartheta_2 = \frac{\partial ERGHG_{i,t}}{\partial ENEF_{i,t}} < 0$, Furthermore, In any debate regarding climate change, renewable energy is frequently near the top of the priority list of improvements that the globe can make to mitigate the worst effects of rising temperatures. This is because renewable energy sources like solar and wind produce no carbon dioxide or other greenhouse gases, which contribute to global warming. Renewables produce more energy than they consume and release less emissions during their lifespan than other power sources. Renewable energy sources create much lower GHGs than fossil-fuel-fired power plants during their lifetimes. ELRE have also negative relation with ERGHG $\vartheta_3 = \frac{\partial ERGHG_{i,t}}{\partial ELRE_{i,t}} < 0$. Similarly, The political risk index, which has 12 elements, analyses the stability of an economy's political system. The greater the political risk, the weaker or more unstable the government, the lower the education rate, poverty, imbalances in access to resources, a risky investment background, and more corrupt politicians and weak institutions. In general, developing nations with significant political risk face a slew of challenges. More corrupt officials, for example, could weaken environmental rules, resulting in illicit manufacturing and increased emissions (Hassan et al., 2022b). While an anti-corruption campaign can serve to reduce corruption and, as a result, environmental degradation (Zhou et al., 2020). So the estimated results of our research show that political risk index has also negative relation with ERGHG $\vartheta_4 = \frac{\partial ERGHG_{i,t}}{\partial PRI_{i,t}} < 0$.

3.2. Econometric strategies

3.2.1. Diagnostic check tests

This test's null hypothesis states that the data are normally distributed, whereas the alternative shows that they are not. Furthermore, the Pesaran and Yamagata (2008) test for heterogeneous slope coefficients and the Pesaran (2004) test for cross-sectional dependency should be used. The use of suitable stationary tests is the next step

after these problems have been established. This test's null hypothesis states that cross-sections are independent and have no spill-over effects. To put it another way, the countries are self-sufficient and immune to local and global economic shocks. Before employing unit root, cointegration, or long-run estimation, it is crucial to discover these difficulties using the econometric tools outlined above. Otherwise, the results (while disregarding these issues) may consequence in biased results.

3.3. Unit root and cointegration check

Examine this paper for stationarity using the Im, Pesaran, cross-sectional augmented, and Shin (CIPS) approach (Pesaran, 2007). The above test may be applied both to cross-sectional dependency and heterogeneous slope coefficients. As a result, this method is preferred over typical panel unit root tests, which solve only one of the two issues mentioned above. The standard equational form for the CIPS test is as follows:

$$\widehat{CIPS} = \frac{1}{N} \sum_{i=1}^N CADF_i$$

(3 (CADF stands for cross-sectionally augmented dickey fuller)

Similarly, Westerlund (2007) uses the (ECM) cointegration technique. As previously stated, this test is effective for obtaining efficient findings even when slope coefficients are diverse and cross-sections are dependent. This test employs four statistics: two panel statistics and two mean group statistics. The following are the equational formulations of each mean group and panel group statistic:

$$G_t = \frac{1}{N} \sum_{i=1}^N \frac{\alpha_i}{SE\alpha_i} \quad (4)$$

$$G_t = \frac{1}{N} \sum_{i=1}^N \frac{T\alpha_i}{\alpha_i(1)} \quad (5)$$

$$P_t = \frac{\alpha}{SE(\alpha)} \quad (6)$$

$$P_t = T\alpha \quad (7)$$

The method of moments quantile regression (MMQR) is described in detail in the next section.

3.4. Method of moments quantile regression (MMQR)

The data in this study is non-normally distributed, according to the normality check. As a result, Machado and Silva's (2019) Moments Quantile Regression (MMQR)

technique may be applied. The fundamental quantile regression method is non-normality resistant, but still it avoids the problem of unobserved variability within the individual panel. In addition, when paired with the Political Risk Index and GDP, this method can be used to quantify the conditionally heterogeneous covariance effect of EE and RE electricity on Energy-Related Greenhouse Gases. Individual effects can now have an effect on the overall distribution (Ike et al., 2020). This strategy is equally useful when the model comprises endogenous independent variables (Anwar et al., 2021). The generic equational version of the MMQR method is as follows:

$$Q_y (\tau / X_{it}) = (\sigma_i + \vartheta_i q(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \tag{8}$$

where, X_{it} Contains all independent variables such as EE, Electricity from RE, political risk index and GDP. $Q_y (\tau / X_{it})$ is the quantile distribution of conditional distribution of Energy-Related Greenhouse Gases on X_{it} . $\sigma_i + \vartheta_i q(\tau)$ is scalar coefficient indicating quantile fixed effect τ for each cross-sections i . Moreover, $q(\tau)$ is for the quantile calculated via τth optimisation problem as follows:

$$\text{Minimise } q \sum_i \sum_t p\tau(R_{it} - Z'_{it}\gamma q(\tau)) \tag{9}$$

Here, $p\tau$ is check function denoted as, $p\tau (A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$.

Furthermore, the robustness tests in this work are carried out using a basic quantile regression technique. In addition, the panel causality test (Dumitrescu & Hurlin, 2012) is used to examine the causal impact of EE and RE Electricity on Energy-Related Greenhouse Gases when combined with the Political Risk Index and GDP.

4. Results and discussion

In this section, Stata-13 and Eviews-1 were used to achieve the results. The empirical results acquired using various economic and statistical tests are presented.

Table 1 empirical results show the average values, volatility, and range for each variable, as well as a normality check. The findings show that Energy-Related Greenhouse Gases, followed by EE, Electricity from RE and GDP are volatile. Moreover, Jarque-Bera (JB) results show that the data is not normally distributed, refuting the null hypothesis of normal distribution for ERGHG, EE, Electricity from RE, and GDP. The results are statistically significant at many levels, notably 1%, 5% and 10% with each variable.

Furthermore, the lower part of Table 1 with values of 4.764*** and 5.694*** correspondingly shows the empirical outcomes of BRICS economies has heterogeneous slope coefficients as directed by $\Delta \sim$ and $\Delta \sim$ **Adjusted**. This shows that these countries are not homogenous and there is heterogeneity in the EE, Electricity from RE, GDP, political risk index and ERGHG. Similarly, the cross-section dependence test results are shown in the lower area of the Table. The findings support the BRICS economies' cross-sectional reliance. This implies that in the present day, independence is unusual, and the bulk of economies are interdependent. The results of this study's unit root test are shown in Table 2 in the following step.

Table 1. Descriptive statistics.

	ERGHG	GDP	ENEF	ELRE	PRI
Mean	2006328.	2.45E + 12	5.954429	2.439211	62.30319
Median	1060509.	1.37E + 12	5.152808	1.236578	63.52083
Maximum	9558575.	1.43E + 13	11.00072	12.11841	70.62500
Minimum	278867.4	2.03E + 11	1.615754	0.009356	32.50000
Std. Dev.	2566122.	3.13E + 12	2.562872	2.951075	7.256132
Skewness	1.836875	2.286544	0.550290	1.422270	-2.414081
Kurtosis	5.186734	7.456055	2.168700	4.517091	9.964396
Jarque-Bera	76.15934	169.8732	7.926410	43.30407	299.2249
Probability	0.000000	0.000000	0.019002	0.000000	0.000000
Diagnostic Tests					
Heterogeneity/Homogeneity Check					
Statistics		$\sim \Delta$		$\sim \Delta_{Adjusted}$	
		4.764***		5.694***	
Cross – Sectional Dependence					
ERGHG		GDP		ENEF	
	5.178***		13.656***		13.585***
ELRE		PRI			
	11.207***		3.918***		

Note that the significance levels for 1%, 5%, and 10% are shown by the letters ***, ** and *.
Source: Author's own calculations.

Table 2. Unit root test.

Statistics	Trend and Intercept	
	I(0)	I(1)
ERGHG	-3.817***	-
GDP	-2.399	-3.337***
ENEF	-1.846	-4.256***
ELRE	-1.094	-3.263***
PRI	-1.648	-3.464***

Note that the significance levels for 1%, 5% and 10% are shown by the letters ***, ** and *.
Source: Author's own calculations.

Table 2 shows the empirical findings of the cross-sectionally augmented Im, Pesaran and Shin (CIPS) test. According to the results of these unit root tests, both unit root tests were performed in two different forms, such as first difference and second difference. Furthermore, case I demonstrates the use of unit root tests with intercept, whereas case 2 includes both intercept and trend. This test's results are unaffected by heterogeneity or cross-sectional dependence. All variables are non-stationary at the level, according to the findings. This suggests that these variables' means aren't returning to zero. Furthermore, the variation in EE, RE Electricity, Energy-Related Greenhouse Gases, GDP and political risk index is not constant. This suggests that these factors vary depending on the cross-section. As a result, all variables are stationary at I(1). A cointegration test is then carried out.

The outcome of a cointegration test based on an error correction mechanism (ECM) is shown in Table 3. Gt, Ga, Pt and Pa are the outcomes of the group and pane statistics. Table 3 shows the results of VECM, which were exclusively used to find long-run causality between the variables. The variable exhibits a long run causal relationship with all other variables, as evidenced by a negative and significant coefficient of ECM. The results show that EE, RE Electricity GDP, political risk index, and Energy-Related Greenhouse Gases have a long-run cointegrating relationship. The

Table 3. Cointegration testing.

Statistics	Value	p – value
G_t	–3.142***	0.006
G_a	–8.094	0.713
P_t	–11.008***	0.000
P_a	–13.544**	0.012

Note that the significance levels for 1%, 5% and 10% are shown by the letters ***, ** and *.

Source: Author's own calculations.

Table 4. Method of moments quantile regression (MMQR).

Variable(s)	Location	Scale	$Q_{0.25}(p - \text{value})$	$Q_{0.50}(p - \text{value})$	$Q_{0.75}(p - \text{value})$	$Q_{0.90}(p - \text{value})$
GDP	1.075***	–0.013	1.085*** (0.000)	1.071*** (0.000)	1.062*** (0.000)	1.057*** (0.000)
ENEf	–0.878***	0.0798	–0.940*** (0.000)	–0.859*** (0.000)	–0.803*** (0.000)	–0.778*** (0.000)
ELRE	–0.108***	0.0203	–0.124** (0.048)	–0.103*** (0.003)	–0.089*** (0.000)	–0.083*** (0.002)
PRI	–0.637***	0.0159	–0.649 (0.184)	–0.633** (0.017)	–0.622*** (0.001)	–0.617*** (0.003)
Constant	–5.26***	0.1869	–5.413*** (0.000)	–5.223*** (0.000)	–5.092*** (0.000)	–5.033*** (0.000)

Note that the significance levels for 1%, 5% and 10% are shown by the letters ***, ** and *.

Source: Author's own calculations.

results are consistent with those of (Khan et al., 2020). On the other hand, this study's output included RE Electricity and Energy-Related Greenhouse Gases in the model. The study then continues to determine the findings of the method of moments quantile regression (MMQR).

The findings of the MMQR technique for the 25th, 50th, 75th, and 90th quantiles are shown in Table 4. The data show that at the 25th quantile, a 1% increase in GDP results in a 1.085% upsurge in ERGHG. The GDP and environmental pollution relationship is similar with Wahab (2021) and Hassan et al. (2022b), the effect of Energy efficiency increases in all quantiles. The link between ERGHG emissions and Energy efficiency, on the other hand, is negative and meaningful only for higher quantiles (25th to the 90th). This demonstrates that Energy efficiency has a positive impact on lowering energy-related greenhouse gas emissions. As mentioned in Table 4, 1% increase in ENEf at the 25th quantile can result in a –0.940 per cent decrease in ERGHG. Alike Wahab et al. (2022), Similar with Wahab et al. (2021) and Chen et al (2018) Similarly, As shown in Table 4, the effect of renewable energy increases in all quantiles. The link between energy-related greenhouse gas emissions and renewable energy, on the other hand, is negative and meaningful only for higher quantiles (25th to the 90th). This demonstrates that renewable energy has a positive impact on lowering energy-related greenhouse gas emissions. moreover, a 1% increase in Electricity from ELRE can result in a –0.124 per cent reduction in Energy-Related Greenhouse Gases. Similarly, at the 25th quantile, the average decline in ERGHG due to increasing political risk index is –0.649 per cent.

Similarly, the output reveals that EE, RE Electricity, and political risk index cause ERGHG to fall at the 50th, 75th, and 90th quantiles. The average rise induced by GDP in the 90th quantile is 1.057 per cent. On the other side, EE resulted in a –0.778 per cent decline in ERGHG. Furthermore, at the 90th quantile, Electricity from RE reduces Energy-Related Greenhouse Gases by –0.083 per cent. Furthermore,

Table 5. Robustness check using mean group (MG) test.

Variable(s)	Coefficients
GDP	0.716***
ENEf	-0.106***
ELRE	-0.060***
PRI	-0.235***
Constant	-2.168***

Note that the significance levels for 1%, 5% and 10% are shown by the letters ***, ** and *.
Source: Author's own calculations.

Table 6. Dumitrescu-Hurlin panel causality test.

H ₀	Wald _{Stats}	\bar{Z}_{Stats}	p – value
GDP – ERGHG	9.652***	10.53	0.000
ERGHG – GDP	3.148**	2.48	0.013
ENEf – ERGHG	8.061***	8.56	0.000
ERGHG – ENEf	5.142***	4.23	0.000
ELRE – ERGHG	5.818***	5.78	0.000
ERGHG – ELRE	6.256***	6.32	0.000
PRI – ERGHG	4.961***	3.01	0.000
ERGHG – PRI	4.316***	3.92	0.000

Note that the significance levels for 1%, 5% and 10% are shown by the letters ***, ** and *.
Source: Author's own calculations.

the political risk index reduces energy-related greenhouse gas emissions by -0.617% (Hassan et al. 2022). Following the theoretical framework, the total outcome for the 25th, 50th, 75th and 90th quantiles suggests that EE, Electricity from RE, and political risk index cause ERGHG to drop. Furthermore, rising GDP leads to an increase in ERGHG. Furthermore, the results for the 25th, 50th, 75th, and 90th quantiles are statistically significant at the levels of 1%, 5%, and 10%, respectively. [Figure 1](#) further confirms these findings. Furthermore, the findings support the theory of a negative influence of EE, RE Electricity and political risk index on Energy-Related Greenhouse Gases.

[Table 5](#) displays the quantile regression results, which was used to assess the robustness of the MMQR findings. The empirical results of quantile regression demonstrate a negative link between EE, RE Electricity and political risk index with Energy-Related Greenhouse Gases at the 25th, 50th, 75th and 90th quantiles. Similarly, the robustness output verifies the positive relationship between GDP and ERGHG at the 25th, 50th, 75th, and 90th quantiles. Furthermore, the results are robust and statistically significant at traditional 1%, 5%, and 10%.

The outcome of the Dumitrescu-Hurlin panel causality technique is shown in [Table 6](#). In the same way, any policy that focuses on EE, RE, GDP and political risk index will impact ERGHG. Furthermore, there is a bidirectional causal link between ERGHG and EE, RE Electricity, GDP, and political risk index. Similarly, the results are strong and statistically significant at traditional 1%, 5%, and 10%.

5. Conclusion and policy implication

Many of the researchers have discussed the environmental problems extremely, However, the role Energy efficiency and Electricity production from renewable sources has been overlook in term of Energy-related greenhouse gases. Therefore, the present study examined the impact of EE and RE on energy-related greenhouse gas

emissions in the BRICS countries between 2000 and 2019. The influence of GDP and political risk index on energy-related greenhouse gas emissions are also examined in this study. Moment Quantile Regression (MMQR), Pesaran slope heterogeneity, panel unit root and cross-section dependency tests, as well as the Westerlund error correction mechanism (WECM) test and Dumitrescu Hurlin panel causality test, were all employed in the study.

The empirical findings began with the Jarque-Bera (JB) normality test, which revealed that the data is non-normally distributed and that utilising parametric results will result in biased results, recommending the use of the moment quantile regression approach (MMQR). Furthermore, the findings revealed that cross-sections had varied slopes and dependencies. The panel unit root test also confirmed the non-stationarity of data at the level for all variables. The long-run cointegrating relationship between EE, RE Electricity, GDP and PRI with ERGHG has also been proven.

The method of moment quantile regression (MMQR) test confirmed a negative relationship for EE, Electricity from RE and PRI with ERGHG is also confirmed. However, GDP has a positive relationship with ERGHG. The results further show that the magnitude of each coefficient increases with each quantile, i.e., 25th, 50th, 75th, and 90th, respectively. The causality test shows that any policy targeting GDP, EE, Electricity from RE and PRI will affect ERGHG.

In terms of policy implications, the study suggests that the BRICS economies should reduce regulatory hurdles to the use of EE technology to benefit the RE industry in the BRICS countries. Finally, the BRICS countries should expand their RE research and development investment. To meet industrialisation's energy demands while simultaneously lowering energy-related greenhouse gas emissions, they need to invest more in RE. Additionally, policymakers should reconsider the asymmetric behaviour of EE, RE and GDP when establishing energy, environmental, and economic growth policies.

Last, Because the consequences of the study are limited to the BRICS nations, the outcome of this study cannot be applied to other countries. A study like this could be done for a number of other nations. Based on the study's asymmetric findings, future research might delve into the nonlinear behaviour of the energy, growth, and environment nexus. The asymmetric NPARDL may be used in a single framework with quantile regression to integrate regional asymmetries. Furthermore, for each country, we used a short sampling period (2004–2019) in this analysis. This was due to the fact that only annual data was available. A possible extension of this paper would be to look for less readily available quarterly data, which could provide more dependable results with more precision and power.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. BRICS countries list includes Brazil, Russia, India, China and South Africa.
2. <https://stats.oecd.org/#>
3. <https://www.prsgroup.com/explore-our-products/international-country-risk-guide/>

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