Power Generation Sources and Carbon Dioxide Emissions in BRICS Countries: Static and Dynamic Panel Regression

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Abstract

Purpose: The threat of global warming has escalated as a result of industrialization, urbanization, population growth, and lifestyle changes in Brazil, Russia, India, China, and South Africa (BRICS). The amount of electricity generated by various sources is directly influenced by their respective carbon dioxide (CO_2) emissions. This study's primary goal is to determine which sources are bad for the environment and which are not.

Methodology: Examining the impact of different energy generation sources on CO_2 emissions using data from the BRICS. To analyze the data, pooled OLS and Generalized Method of Moments (GMM) are used, as well as Quantile Regression (QR).

Findings: We found that coal and gas power generation had a positive

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and large influence on CO_2 emissions regardless of the method used. As compared to other emissions, coal-fired energy production has a more significant impact. In all regression models, hydroelectric and renewable energy generation can reduce CO_2 emissions.

Originality: Identifying an empirical link between CO_2 emissions and energy production sources is the study's most significant accomplishment. To obtain solid results, the paper used a combination of QR and GMM techniques. The conclusions presented in this article have important environmental policy consequences. CO_2 emissions can be reduced by reducing the consumption of fossil fuels and promoting the development of alternative energy sources such as hydroelectric, wind, and solar power.

Keywords: BRICS, climate change, CO_2 emissions, electricity production sources, energy consumption.

1 Introduction

In the 21st century overall human civilization has reached the peak of economic growth and development. The driving force for reaching such unbelievable growth and development are possible by electricity which is generated from the consumption of different renewable and nonrenewable energy. Consumption of energy increase and intensify the concentration of CO_2 and other greenhouse gases in the global atmosphere which deteriorated the ambient quality of the global environment as well as ecological biodiversity. The threat of global warming has intensified in recent decades due to rising levels of modernization, a rapidly expanding global population, a shift in the way people live, and an increase in the amount of electricity they use. To meet up the growing demands for electricity and mitigate the CO_2 emissions and other greenhouse gases this study tries to focus on the link between electricity production sources and CO_2 emissions. The BRICS members stated that "global warming has become one of the big hurdles and hazards to achieving the sustainable development goals" during the Fifth BRICS Summit in Durban in March 2013 (Fifth BRICS Summit, 2013). The recent economic expansion of BRICS countries has been achieved through continuing to utilize substantial amounts of fossil fuels for electricity production, leading to greater global warming. For the execution of associated regulations, the direction of causation between power generating sources and CO_2 emissions is critical. If, for example, renewable energy sources reduce CO_2 emissions, the government would instead need to invest in improving electrical efficiency to reduce emissions. The government will take different alternative strategies to amend the level of each variable if no causation exists between these variables. However, if any bidirectional causality or mutual influence exists in any of these variables, the government must take into account the policies to the modification of each variable that one would have an impact on others. The multiple adverse effects of rising CO_2 have been a prominent issue in environmental, health, and development economics in this century. Because of their manufacturing, industrial, and service-oriented economies, the BRICS countries consume a lot of energy. The BRICS countries will dominate the global economy by 2050 because they are the fastest expanding economies in the world economy with a combined GDP of 20 trillion US dollars and their average GDP growth rate is 6% per year. However, the rapid economic expansion of BRICS countries is frequently accompanied by an increase in energy use, which can have unintended consequences for the environment and energy assets. Scientific evidence has shown that CO_2 emission is the leading greenhouse gas responsible for almost 80% of the greenhouse gases that cause global warming, climate change, and the greenhouse effect. In 2021, more than 40% of the world's population lives in BRICS countries. This massive population size provides a versatile and larger consumer market for goods and services. However, excessive population means huge consumption and excessive use of energy that increases CO_2 emissions. Though a lot of earlier studies only looked at the impact of financial development, population, GDP, and consumption on CO_2 emissions using a panel or time-series data. To our knowledge (Abdallah and El-Shennawy, 2013) has examined the impact of electricity production sources on CO_2 emissions at the sub-component level. Our empirical analysis reveals the impact of electricity production sources on CO_2 emission, while it is widely proved that power production has a positive connection with carbon emissions, while electricity production from different sources increases carbon emissions and economic growth. Since the 1990s rapid globalization has created a significant impact on social, political, and economic elements of human life. A country can continue and boom its development through international trade, free flows of capital, and foreign direct investments (FDIs) (Gasser, 2020). In 2012, a Guardian report exposed that India was the 4th largest economy in the world and its position was 3rd for CO_2 emissions from energy consumption in the world. As a result, because literature evaluations show that power production and CO_2 emissions are linked, including CO_2 in our model is critical. Furthermore, from an academic and research standpoint, we found that just a few studies used GMM and quantile regression methodologies (Bashir et al. 2020). Based on what we know thus far, there is very little panel data research in this BRICS region applying GMM and QR methods. The remainder of the article, it is structured as follows: A overview of the literature is presented in Section 2. Section 3 details the study's data and methods. Section 4 analyzed the regressions and their outcomes. Conclusion and policy implications can be found in Section 5, the final section of the paper.

2 Literature Review

However, the massive consumption of various energy sources, as well as their effects on CO_2 emissions are posing a serious threat to current and future generations. Droughts, glacier melt, increasing sea levels, global warming, and heatwaves are already a reality in many parts of the planet. These negative effects on the environment put the environment in jeopardy. Studying the ecological footprint of the BRICS economies between 1992 and 2018, (Abraham et al. 2022) studied the impact of biomass energy consumption on the ecological footprints of the BRICS economies. Globalization and the use of biomass energy lessen environmental degradation in all quantiles (10th to 90th), but an economic expansion, natural resources, and the creation of gross capital contribute to environmental degradation. From 1992 to 2013, BRICS countries' data was utilized by Mucahit Aydin (2019). There was a focus on the impact of biomass energy use on economic development. Heterogeneous panel data analysis was utilized to draw inferences and produce outcomes tailored to various countries. Consumption of biomass energy is critical in fostering economic growth and decreasing reliance on imported energy. Individual heterogeneity and the omitted-variable bias were overcome using Panel quantile regression by Wenhui et al. (2018) for estimating the causes of CO_2 emissions. CO_2 emissions are reduced the most by using non-renewable energy, according to their research. High-emission countries have a limited role in renewable energy, which has a significant impact on countries with greater emissions. Aytekin (2022) applied ARAT, CRITIC, SOWIA, CRADIS, and CODAS-Sort, his study intends to analyze countries on the basis of energy, environment, and sustainability triangle. The results suggest that industrialized countries are in a better situation than developing and underdeveloped countries in terms of sustainable energy and environmental issues. The goal of Yu et al. (2019) is to assess the impact of energy generation on industrial development and long-term economic growth. Countries with the largest increases in power generation between 2000 and 2018 are included in this study's scope. According to the findings, power production in the BRICS countries has a beneficial impact on industrial production and sustainable economic growth over the period from 1991 to 2018. Cowan et al. (2013) use panel causality analysis to reevaluate the causative relationship between electricity consumption, economic development, and CO_2 emissions in the BRICS nations from 1990 to 2010, allowing for dependence and heterogeneity among countries. They discover that policies for the BRICS nations cannot be executed consistently since they would have varied consequences in each of the BRICS countries under consideration. Baloch et al. (2019) looked at the impact of abundant natural resources on carbon dioxide (CO_2) emissions. The analysis includes annual panel data from BRICS nations from 1990 to 2015. They discovered that while abundant natural resources reduce CO_2 emissions in Russia, they also add to pollution in South Africa. Finally, causality analysis indicated that natural resources and CO_2 emissions had a reverse relationship. Mulali (2014) focused on the impact of nuclear energy consumption on GDP growth and CO_2 emissions in 30 of the world's most populous nuclear-power nations. For the years 1990–2010, the panel mode was employed. According to the findings, nuclear energy use has a favorable long-term influence on GDP growth but has no long-term impact on CO_2 emissions. The study's findings led to several suggestions for the nations under investigation.The elements that have impacted the level of energy-related CO_2 emissions were discovered by Paul and Bhattacharya (2004). The observed changes are decomposed into four factors: pollution coefficient, energy intensity, structural changes, and economic activity, using the decomposition approach. From the years 1980 to 1996, the research looks at India's key economic sectors.Finally, it was discovered that energy intensity changes over a larger range and has a stronger influence on energy-induced CO_2 emissions than the pollution coefficient. Academics and the Chinese government support electrification as a means of reducing pollution and increasing production. However, when converting from different fuels to electricity under governmental assistance, the challenge of how to achieve the trade-off between lowering CO_2 emissions and preserving economic development remains unsolved shown by Zhao et al. (2018). And it was shown that practically all exogenous shocks in fuel demand have positive effects on both GDP and CO_2 emissions, as well as that various electric appliances for electrification, have highly varied CO_2 emission reduction consequences. Zhang et al. (2009) studied the nature of the variables that influence variations in energy-related CO_2 emissions and CO_2 emission intensity between 1991 and 2006. Among other things, they examined the factors that influence changes in energy-related CO_2 emissions and the intensity of CO_2 emissions. According to their findings, the most important factor in decreasing CO_2 emissions and intensifying CO_2 emissions was the effect of energy intensity, the most important factor in increasing CO_2 emissions was the effect of economic activity, and the economic structure and the CO_2 emission coefficient had only a small impact on these changes. There is a strong correlation between short-term CO_2 emissions and energy use and production, according to Pao and Tsai (2010). There is a significant bidirectional relationship between energy use and CO_2 emissions, also between energy consumption and actual production. Consequently, the expansion of the BRICS nations is heavily dependent on energy.When it comes to emissions and FDI as well as energy consumption and output, Pao and Tsai (2011) found evidence of bidirectional causality in each of these domains as well as a connection between energy use and output. FDI and production have been found to have long-run unidirectional causality in both directions. A two-way causal link was found in the emissions-to-FDI nexus.Thus, BRICS nations must increase their investments in electricity generation and push the industry to embrace innovation to minimize emissions while ensuring their long-term sustainability. In the opinion of Dantama et al. (2012), electricity influences all aspects of development, including financial, social, and even first-class lifestyles in the developing world. It was also discovered, according to Urry (2015), that an increase in the amount of CO_2 and other greenhouse gases in the atmosphere is to blame for these calamities, and that they had also collected data on rising temperatures on land and at sea. Rahman (2017) calculated that greenhouse gas absorption increased by 34 percent between 1990 and 2013, based on data from eleven Asian populous countries. CO_2 emissions accounted for over 80 percent of this increase. Even after attaining a highly developed economy, electrification has taken place in all areas of the industrial and service sectors in South Korea, one of the Asian tigers, resulting in a continual expansion of the concentration of energy resources. Also contributing to increased electrification in manufacturing sectors where the development and expansion of the Information and Communication Technology (ICT) industry as well as cheap electricity rates. Moreover, In addition, they discovered a favorable association between electrification and harmful gas emission levels (Cho, 2007; Yoo, 2005). Since 1990, China's energy consumption has increased in tandem with the growth of the country's major industries, which include manufacturing, raw materials, mining, and chemicals. Additionally, it has significantly increased electrification in all industries and families within three decades (Wang et al., 2010). There seems to be no research on the causal link between power generating sources and carbon emissions in the BRICS nations that we are aware of.This study attempted to close the void in the existing literature. Moreover, in our study, we applied system GMM and Difference GMM as well as the Quantile Regression approach to identify some useful insights about CO_2 emissions from different electricity production sources in BRICS countries which was not been done yet by any researcher simultaneously.

3 Methods of the Study

3.1 Data and Variables of the Study

The annual panel data were collected from 1971 to 2019 from the World Development Indicators (WDI), the World Bank database for five giant economies. Our variables are listed here:

3.2 Econometric Model Specification

Our independent variables include electricity produced by coal, natural gas, nuclear, hydroelectric, oil, and renewable sources (excluding hydroelectric

Table 1 Introduction of selected variables

Name of the Variables	Variables in Log Form	Elaboration of the Variables	Sources
CO_2	*$L(CO_2)$*	CO_2 emissions (kt)	*WDI*
Coal	*L(Coal)*	Electricity generated by coal sources (% of overall electricity production)	*WDI*
Gas	*L(Gas)*	Electricity generated by gas sources (% of overall electricity production)	*WDI*
Nuclear	*L(Nuc)*	Electricity generated by nuclear sources (% of overall electricity production)	*WDI*
Hydro	*L(Hydro)*	Electricity generated by hydroelectric sources (% of overall electricity production)	*WDI*
Oil	*L(Oil)*	Electricity generated by oil sources (% of overall electricity production)	*WDI*
Renewable	*L(Renew)*	Electricity generated by renewable sources (% of overall electricity production)	*WDI*

Source: WDI (2021).

Table 2 Synopsis of descriptive statistics

Variables	N	Mean	St. Dev.	Min	Max
L(CO_2)	245	3.599	0.518	2.361	4.274
L(Coal)	245	3.385	1.284	0.510	4.603
L(Gas)	245	1.041	1.379	−1.922	3.917
L(Oil)	245	0.650	1.749	−6.360	3.310
L(Renew)	245	−0.711	1.839	−6.927	2.495
L(Hydro)	245	2.569	1.554	−2.474	4.536
L(Nuc)	245	1.105	0.822	−3.856	2.834

Source: Authors' Calculations.

sources) on CO_2, and the paper used the well-known methodological technique. The following Equation (1) may be used to determine the influence of dependent and independent variables:

$$CO_2 = f(\textit{Coal, Gas, Oil, Renew, Hydroelectric, Nuclear}) \tag{1}$$

The important notification is that this study excluded dummy variables, all are categorical variables. This is because the behavior of data is assumed not to fluctuate over time.

Now, the multivariable econometric model is that:

$$\begin{aligned} CO_{2it} &= \beta_0 + \beta_1 Coal_{it} + \beta_2 Gas_{it} + \beta_3 Oil_{it} + \beta_4 Renewable_{it} \\ &\quad + \beta_5 Hydroelectric_{it} + \beta_6 Nuclear_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

The log transformation has been taken in Equation (3).

$$\begin{aligned} L(CO_2)_{it} &= \beta_0 + \beta_1 L(Coal)_{it} + \beta_2 L(Gas)_{it} + \beta_3 L(Oil)_{it} \\ &\quad + \beta_4 L(Renew)_{it} + \beta_5 L(Hydro)_{it} + \beta_6 L(Nuc)_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

Where,β_0 is the intercept term.$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$, and β_6 are the slope coefficients. The ε is present the residual, and i presents the cross-section country, t presents the time.

The descriptive statistics for each variable are shown in Table 2. The mean, number of observations, standard deviation, minimum, and maximum values are all represented. CO_2 has a greater mean value than the other variables. We may do a preliminary examination of the variables using descriptive analysis.

3.2.1 GMM approach

To reach a study purpose, a variety of econometric approaches are used. To determine whether the combination of energy production from multiple sources has a substantial impact on CO_2 emissions, we will use a methodical approach that will direct us along a clear path. To estimate dynamic panel estimators in our research, we applied the generalized method of moments (GMM), specifically the one-step system GMM which was developed by Arelleno and Bover (1995) and Blundell and Bond (1998), and the difference GMM which was developed by Arollano and Bond (1991). A variety of factors influenced our decision to use this methodology. Roodman (2009) said that both system GMM estimates and difference GMM estimates work well when the time series (T) is shorter than the cross-sectional unit (N). When there is a linear relationship between the variables, the panel data is not balanced, a single dynamic dependent variable is correlated with its past value, and explanatory variables are not strictly exogenous, which means they are correlated with their present and past value of error, if there is autocorrelation, heteroscedasticity, and fixed individual effects within a cross-section unit but not across them.. The endogeneity of the explanatory variables can be dealt with using the system GMM technique. This method evaluates both the first difference and the level of the equation simultaneously. Explanatory variables in the first difference equation are instrumented using lagged regressor values. Improving the model, and instrumental factors assist remove endogeneity from explanatory variables by using this distinction. In addition, the system GMM technique is more efficient and consistent than other GMM econometric techniques (Baltagi 2008). The expected association between the error term and country fixed effects was also handled by this strategy. Because of the limited time and cross-sections in dynamic penal data, the problem is particularly acute (Nickell, 1981). The following is the specification for the system GMM technique in the level and differenced form formats:

$$
\begin{aligned}
L(CO_2)_{it} = \beta_0 &+ \beta_1 L(CO_2)_{it-1} + \beta_2 L(Coal)_{it} + \beta_3 L(Gas)_{it} \\
&+ \beta_4 L(Oil)_{it} + \beta_5 L(Renew)_{it} \\
&+ \beta_6 L(Hydro)_{it} + \beta_6 L(Nuc)_{it} + \varepsilon_{it} \qquad (4)
\end{aligned}
$$

Differences GMM:

$$
L(CO_2)_{it} - (CO_2)_{it-1} = \beta_0 + \beta_1 (L(CO_2)_{it-1} - L(CO_2)_{it-2})
$$

$$
\begin{aligned}
&+ \beta_2(L(Coal)_{itit} - L(Coal)_{it-1}) \\
&+ \beta_3(L(Gas)_{it} - L(Gas)_{it-1}) \\
&+ \beta_4(L(Oil)_{it} - L(Oil)_{it-1}) \\
&+ \beta_5(L(Renew)_{it} - L(Renew)_{it-1}) \\
&+ \beta_6(L(Hydro)_{it} - L(Hydro)_{it-1}) \\
&+ \beta_7(L(Nuc)_{it} - L(Nuc)_{it-1}) \\
&+ (\eta_t - \eta_{t-1}) + (\varepsilon_{it} - \varepsilon_{it-1})
\end{aligned}
\tag{5}
$$

3.2.2 Quantile regression (QR regression)

An important application of the quantile regression methodology is in studying non-normally distributed and nonlinearly correlated outcomes and their nonlinear interactions with predictor factors.

Buchinsky (1994) points out that, To describe the feasible heterogeneous impacts, we identify the qth-quantile (0 < q < 1) of the dependent variable as impermanent distribution, given a set of X_i variables, as follows:

$$
Q_q(y_{it}|\beta_0, \varepsilon_{it}, x_{it}) = \beta_0 + \varepsilon_{it}^q + \beta_i^q x_{it} \tag{6}
$$

Where y_t the CO_2 emission through time is, u_t signify for unobservable factors. A vector of independent variables (X_{it}) is also included. Cameron and Trivedi (2010) demonstrated that Equation (6) inference based on the qth quantile regression requires the minimization of the residual's absolute value using the subsequent objective function:

$$
\begin{aligned}
Q(\beta_i^q) &= \min \beta \sum_{q,i,t=1}^{n} ||y_{it} - x_{it}\beta_i^q|| \\
&= \min \left[\sum_{i:y_{it} \geq x_{it}\beta} q|y_{it} - x_{it}\beta_i^q| + \sum_{i:y_{it} < x_{it}\beta} (1-q)|y_{it} - x_{it}\beta_i^q| \right]
\end{aligned}
\tag{7}
$$

There are two parts to Canay's (2011) assessment approach. In the first step, the mean of u_t is calculated. Quantile regression is then used to evaluate this component after subtracting it from its original dependent variable.

4 Empirical Results

Correlation analysis is essential to our study because we need to determine whether there is a positive or negative relationship between variables. Positive covariance arises when two variables are positively related to one another. When two variables are connected oppositely, negative covariance is formed. In Table 3, L(Coal), L(Gas), and L(Nuc) are positively correlated with L(CO_2). L(CO_2) and L(Coal) have the greatest and most significant positive connection, whereas L(CO_2) and L(Hydro) have the lowest and least significant negative correlation (−0.705). Between any of the research variables, there are no correlation coefficients larger than 0.80. This indicates that the study's variables are not in any manner interconnected, and there is no multicollinearity. Among the positive correlation with L(CO_2) while gas-fired power generation has the lowest value (0.395). L(Oil), L(Renew), and L(Hydro) has negatively correlated with L(CO_2). L(Coal), on the other hand, has a negative association with L(Oil), L(Renew), and L(Hydro), with values of −0.298, −0.248, and −0.696, respectively. L(Oil) and L(Renew) also have an inverse correlation, with a value of −0.054.

To evaluate whether the dependent and independent variables are stationary or non-stationary, panel data analysis uses the panel unit root test. In the literature, panel unit root tests appear in several forms. For the unit root test on the dependent and independent variables, data is supplied as a level or beginning difference in Table 4. H_0 is a non-stationary process with a unit root, while H_1 is a stationary process with no unit root. I(1) or the first difference is the stationary point for all variables, according to the Table 4. It is also permanently located at the first difference level, where data from one period to the previous period was adjusted. According to the results, the

Table 3 Correlation for the variables

Variables	L(CO_2)	L(Coal)	L(Gas)	L(Oil)	L(Renew)	L(Hydro)	L(Nuc)
L(CO_2)	1.000						
L(Coal)	0.735***	1.000					
L(Gas)	0.395***	−0.093	1.000				
L(Oil)	−0.215***	0.58***	0.154	1.000			
L(Renew)	−0.497***	−0.248***	−0.322***	−0.054	1.000		
L(Hydro)	−0.705***	−0.696***	−0.103*	0.651***	0.175***	1.000	
L(Nuc)	0.488***	0.189***	0.642***	−0.128**	−0.407***	−0.340***	1.000

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' Calculations.

Table 4 Unit root test result

Variables	At Level			At 1st Difference		
	Harris-Tzavalis	Im-Pesaran-Shin	Levin, Lin & Chut	Harris-Tzavalis	Im-Pesaran-Shin	Levin, Lin &Chut
L(CO_2)	0.448	0.726	−0.471	−30.35***	−8.765***	−5.613***
L(Coal)	1.447	2.294	4.70	−32.44***	−9.13***	−7.29***
L(Gas)	−0.94	1.145	.362	−32.10***	−8.956***	−5.15***
L(Oil)	−1.236	−0.863	−0.073	−38.19***	−9.33***	−7.88***
L(Renew)	−0.98	−0.736	−0.559	−31.83***	−9.177***	−7.82***
L(Hydro)	−1.11	0.617	0.545	−39.52***	−9.769***	−7.72***
L(Nuc)	−2.18	−1.054	−1.028	−44.82***	−10.75***	−9.687***

Note: 1%, 5%, 10% significance level denoted by ***, ** and * respectively. Presume as trend and intercept.
Source: Authors' Calculations.

null hypothesis is rejected at the 5% significance level in the first difference. All variables are classified as stationary when utilizing the first differenced data since P-values are expected to be zero. As a result, there isn't a unit root. When all series are considered stationary variables, the data can now be predicted with a high degree of accuracy for all series at I(1). We expect that both dependent and independent variables will have unit root behavior as a general rule. If the p-value is less than or equal to a particular significance level, such as 0.1 (10 percent) or 0.05, the null hypothesis should be rejected (5 percent).

To evaluate the rationality of results and confirm that the best method is selected for the analysis, we associate different approaches, fixed effect (FE) regression, random effect (RE) regression, generalized method of momentum (Arellano and Bond 1991; Arellano and Bover 1995), and system GMM model, for a sample of 5 BRICS countries. Our primary focus is on the differenced and system GMM approach because it gives us efficient and unbiased results (see for more details methodology part), while other methods are included for comparison purposes. We employed fixed and random effects to compare our results with the previous studies. We also admit that the results are potentially biased and unpredictable due to the omitted variables bias and endogeneity problem that this method is incapable of solving. Difference GMM is used for comparison and robustness purposes with system GMM, and the coefficient sign of differenced GMM is correct with system GMM results and confirms the validity of the results. The dynamic panel model System Generalized Method of Moments, first described by Arellano and Bover (1995) and then by Blundell and Bond (1998), has also been used to deal with the unbalanced panel bias and the potential endogeneity of explanatory variables in our analysis. The system GMM provides more consistent and efficient parameter estimations than panel OLS regressions. To a large extent, this model allows for a wide range of exogeneity for independent variables. The independent variables that are not required to be exogenous are correlated with the current and previous errors. Each group has a reasonable possibility of autocorrelation and heteroscedasticity (Roodman, 2009). In terms of flexibility and reliability of outcomes, this model is superior to the other dynamic panel model. As a result, it is one of the most often employed dynamic panel models to address endogeneity and over-identification of independent variables.

Models 3 and 4 in Table 5 have a positive and highly significant lag value for CO_2 emissions L(CO_2, i, t $-$ 1), indicating a link between the previous year's CO_2 emissions and present levels.

The log-log model, including static and dynamic panel data estimates, is shown in Table 5. The fixed and random impacts of our CO_2 emissions and power generation from various sources are represented by the coefficient of columns 1 and 2 models. To put it another way, the coefficient here represents the percentage change in CO_2 emissions given a percentage variation in the independent variables. The dynamic panel regression of our model is displayed in columns 3 and 4. In the fixed and random effect models, the coefficients of L(CO_2) to explain L(Coal) are 0.206^{***} and 0.234^{***}, respectively, and this estimate is positive and significant. For the Differenced GMM and System GMM models, a 1% rise in L(Coal) leads to CO_2 emissions of 0.0525% and 0.0276%, respectively. That means coal is responsible for carbon emissions (Huang et al. 2018). The dynamic GMM model calculates the intended output in the second phase when L(Coal) and L(Gas) make a significant contribution to boosting CO_2 in a given panel study region. For fixed and random effect models, the variables L(Oil) had negative coefficients of -0.0575^{***} and -0.0491^{***}, indicating that a 1% increase in electricity generation from oil presents a barrier to CO_2 emission of 0.0575 and 0.0491 percent, respectively. CO_2 emissions are also reduced by the factors *L(Renew)* and L(Hydro) (Bilgen et al. 2004). *L(Renew)* has a negative and substantial influence on L(CO_2) in both the fixed and random effect models, with coefficient weights of -0.589^{***} and -0.649^{***}. For the Differenced GMM and System GMM models, a 1% rise in L(Renew) declines to CO_2 emissions of 0.0894% and 0.0407%, respectively. Similarly, in Differenced GMM and System GMM models, a 1% rise in L(Hydro) reduces CO_2 emissions by 0.0109% and 0.0522%. This is also proved by Bayazit (2021). At the same time, empirical estimates indicate that L(Nuc)

Table 5 Dynamic and static panel regression result

Variables	(1) FE	(2) RE	(3) Differenced GMM	(4) System GMM
$L(CO_{2,t-1})$			0.916***	0.915***
			(0.0420)	(0.0505)
L(Coal)	0.206***	0.234***	0.0525***	0.0276*
	(0.0450)	(0.0165)	(0.0112)	(0.0148)
L(Gas)	0.106***	0.132***	0.0105**	0.0136**
	(0.0155)	(0.0139)	(0.00711)	(0.0104)
L(Oil)	−0.0575***	−0.0491***	0.00854*	0.00849
	(0.0112)	(0.0112)	(0.00506)	(0.00768)
L(Renew)	−0.0589***	−0.0649***	−0.00894*	−0.00407*
	(0.00863)	(0.00868)	(0.00467)	(0.00759)
L(Hydro)	−0.116***	−0.0393**	−0.0109*	−0.00522*
	(0.0309)	(0.0172)	(0.00835)	(0.0129)
L(Nuc)	0.0114	0.00218	0.00322	0.00100
	(0.0249)	(0.0245)	(0.0123)	(0.0102)
Constant	3.099***	2.758***	0.0779	0.183
	(0.213)	(0.0956)	(0.120)	(0.178)
Hausman test		18.52**		
AR-1				0.007
AR-2				0.115
Hansen Test			0.682	0.780
Sargan Test			0.150	0.130
R-squared	0.526	0.5125	0.6325	0.7628
Observations	240	240	229	226
Number of Countries	5	5	5	5

Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' Calculations.

contributes to increasing CO_2 emissions in both static and dynamic panel regressions. Similar results were found by Jin & Kim (2018); Ozturk (2017). But some empirical results are conflicted with us because when we use only nuclear energy rather than using renewable energy (Menyah & Wolde, 2010). Haussmann chi-square value in Table 5 is 18.52 when compared to its significance (0.025), which indicates that the Random-effect model is the better choice when compared to fixed effects. The results of the differenced and system GMM model, except for L(Oil), are broadly comparable to those of the fixed and random effect model in terms of significance and direction. For differenced and system GMM estimates to be reliable, it must be assumed

Table 6 Quantile regression

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	OLS	Q_5	Q_{25}	Q_{50}	Q_{75}	Q_{95}
L(Coal)	0.234***	0.236***	0.253***	0.236***	0.247***	0.259***
	(0.0178)	(0.00957)	(0.0297)	(0.00957)	(0.0235)	(0.0217)
L(Gas)	0.132***	0.161***	0.180***	0.161***	0.144***	0.0946***
	(0.0121)	(0.00804)	(0.0249)	(0.00804)	(0.0198)	(0.0183)
L(Oil)	−0.0491	−0.0182	−0.00734**	−0.0182***	−0.0515***	−0.0219
	(0.0121)	(0.00646)	(0.0200)	(0.00646)	(0.0159)	(0.0147)
L(Renew)	−0.0649***	−0.0455***	−0.0314**	−0.0455***	−0.0658***	−0.0650***
	(0.00941)	(0.00502)	(0.0156)	(0.00502)	(0.0123)	(0.0114)
L(Hydro)	−0.0393***	−0.0565***	−0.0649**	−0.0565***	−0.0310	−0.00695
	(0.0144)	(0.00997)	(0.0309)	(0.00997)	(0.0245)	(0.0227)
L(Nuc)	−0.00218	0.0264*	0.0737*	0.0264*	−0.0310	0.0240
	(0.0181)	(0.0142)	(0.0439)	(0.0142)	(0.0348)	(0.0322)
Constant	2.758***	2.761***	2.568***	2.761***	2.848***	2.833^S
	(0.0886)	(0.0554)	(0.172)	(0.0554)	(0.136)	(0.126)
Observations	240	240	240	240	240	240
R-squared	0.833	0.695	0.682	0.611	0.638	0.593

Robust standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Authors' Calculations.

that the error term does not exhibit serial correlation. Consequently, both models show no evidence of serial correlation of the first-differenced error at order 2 by the insignificant values of AR (2). An important factor in GMM estimations is the validity of the instruments used. Over-identifying limitations tests such as the Sargan and Hansen tests are used to assess the overall validity of instrumental variables utilized in the estimation technique. Specifically, the null hypothesis stated that all instruments were exogenous as a group or, more specifically, that all instruments were valid. As demonstrated in this investigation, the Hansen test statistics have probability values of 0.682 and 0.780. On the other hand, Sargan tests statistics have probability values of 0.150 and 0.130 in the present study. Both suggest that the null hypothesis, i.e. that the instruments were valid, was accepted.

The OLS regression of CO_2 emissions and power generation from various sources is shown in Column 1. The regression quantiles are shown in columns 2 through 6. Q_5, Q_{25}, Q_{50}, Q_{75}, and Q_{95} are all considered in the QR model. Coal and natural gas power generation have a positive association with carbon emissions based on empirical evidence. The coefficients of L(Coal) to explain L(CO_2) in the QR models for Q_5, Q_{25}, Q_{50}, Q_{75}, and Q_{95} are 0.236***, 0.253***, 0.235***, 0.247***, and 0.259***, which is a positive

Table 7 Quantile slope equality test

Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test		39.89^{***}	8	0.00
Restriction Detail: b(tau_h) − b(tau_k) = 0				
Quantiles	Variable	Restr. Value	Std. Error	Prob.
0.25, 0.5	L(Coal)	0.492^{***}	0.128563	0.0009
	L(Gas)	0.0568	0.065201	0.7083
	L(Oil)	-0.513	0.096321	0.5125
	L(Hydro)	0.425^{***}	0.096321	0.0021
	L(Nuc)	-0.015^{***}	0.096321	0.0003
	L(Renewable)	-0.048^{***}	0.020676	0.0194
0.5, 0.75	L(COL)	-0.148^{**}	0.077715	0.043
	L(Gas)	-0.295^{***}	0.099587	0.003
	L(Oil)	0.336	0.04982	0.4581
	L(Hydro)	-0.024^{*}	0.099587	0.0905
	L(Nuc)	0.039	0.05155	0.4401
	L(Renewable)	0.054^{***}	0.017243	0.0015

Note: 1%, 5%, 10% significance level designated by ***, ** and * orderly.
Source: Authors' Calculations.

and significant estimation. In terms of carbon dioxide emissions, negative and significant coefficients exist for the variables L(Renew) and L(Hydro). *L(Renew)* coefficients are -0.46^{***}, -0.031^{**}, -0.46^{***}, -0.658^{***}, and -0.0650^{***}, meaning that a one percent increase in *L*(*Renew*) sources provides a CO_2 emission barrier of 0.46, 0.031, 0.46, 0.658, and 0.0650% in different quantiles, respectively. It's also worth that carbon emissions and electricity production from renewable and hydroelectric sources have a statistically significant and negative association. Various quantiles of nuclear energy output were shown to have varying effects on the environment, according to the study. Consequently, reducing carbon emissions is one way to improve environmental quality by using electricity generated from renewables, fossil fuels, and hydroelectricity. Electricity generated from oil sources has a negative impact, albeit it is only statistically significant in the mid-quantiles. Nuclear sources hurt carbon emissions when we run OLS, but a positive and significant effect in most of the quantiles. The variable L(Nuc) has a positive effect in the Q_5, Q_{25}, Q_{50}, and Q_{95} quantiles on CO_2 emissions and the first three quantiles are significant at a 10% level. The OLS model (column 1) and Quantile regression (column 2–6) analyses are shown these results.

The outcome of the panel quantile regression analysis is shown in Table 7. Normality assumes that the underlying residuals are regularly distributed, or roughly so. As a consequence, this research explains the empirical estimates of quantile regressions for the 25th, 50th, and 75th quantiles, with the results provided in Table 7. The L(Coal) coefficients for L(CO_2) are positive for up to 50 quantiles and negative for the higher quantiles, according to the regression estimations. As one progresses from the lower to the middle quantiles, the value rises, then drops as one move to the upper quantiles, although the first to fourth quantiles are statistically significant. On the other hand, we find negative coefficients on the L(Oil) and *L(Renew)* variables over up to 50 quantiles, with all coefficients being statistically significant. The L(Oil) and L(Renew) variables, on the other hand, have positive coefficients from the 50th to the final percentile. All L(Renew) coefficients are statistically significant, however, beyond 50 quantiles, L(Oil) is statistically insignificant.

5 Conclusion

Within the scope of this research, the link between electricity generation sources and CO_2 emissions in five emerging markets will be investigated. This was accomplished via the use of a panel GMM and the quantile regression approach, which were applied to BRICS nations between 1971 and 2019. To empirically assess the impact of various power production sources on CO_2 emissions, the researchers employed quantile regression and generalized linear models (GMM). When compared to other methodologies such as the OLS, GLS, and ARDL models that have been used in similar studies, one step differenced GMM, system GMM, and Quantile Regression provide a more detailed explanation of the overall dependence of energy generation from various sources on CO_2 emissions than do the other methodologies. The more significant production factors of coal and natural gas are due to the increased outputs of these resources. Furthermore, while the size of the relationship is less, there is a negative relationship between renewable energy production and the amount of environmental harm. As a result, power produced from renewable sources is preferred above electricity generated from other sources. When it comes to CO_2 emissions, it has been shown that energy-generating sources are positively associated with the BRICS nations. In a similar vein, power generation from hydroelectric sources has the potential to mitigate environmental harm and has a substantial impact. As a result, power produced from renewable sources is preferred above electricity generated from other sources. When it comes to CO_2 emissions, energy generating sources derived from coal and natural gas were positively and substantially connected in all of our models in the BRICS nations studied. Even though we did not get precise instructions on the power generation from oil sources. The implementation of renewable energy policies in these nations has lagged. Consequently, power production in these countries continues to be heavily reliant on non-renewable sources of energy. It will be shown in this paper that human activities and behaviors have made a significant contribution to the worldwide rise in CO_2 emission levels throughout time as a result of massive energy production, industrialization, economic development, and a constantly growing population. In terms of human health and the environment, this is exceedingly harmful. It is clear from the quantile regression findings that many factors in the research are statistically significant. The majority of the factors examined had a direct impact on CO_2 emissions. The most significant recommendation for the BRICS countries as a whole is increased investment in energy infrastructure. This will allow for an increase in power production capacity to satisfy demand while also boosting the efficiency of energy generation and climate change mitigation policy. Quantitative climate change mitigation strategies can serve a variety of functions, from influencing policy design and execution to monitoring policy performance and justifying budget allocation to attracting climate investment (Sebos et al. 2021). Individually created solutions will be highly valued, as will strategies that consider the general goals of generating and sustaining economic growth and development, energy security, and climate change prevention. A universal "umbrella" general guideline would not have been appropriate since the outcomes for the BRICS nations differed significantly from one another.

Policy Implication and Future Research

A strong correlation between energy production and CO_2 emissions, both in the positive and negative sense, was uncovered during our analysis. Because of this, governments should put their efforts into formulating energy and economic policies that reduce CO_2 emissions while simultaneously improving the environment and promoting sustainable energy sources. Regulations of this type must also be applied without negatively impacting electricity consumption or the expansion of the overall economy of the society. Sustainable environment investment, for example, has been widely regarded as a necessary step in addressing the environmental impacts of CO_2 emissions. Also, there should be no negative impact on energy consumption or economic growth if these guidelines are implemented. For example, climate finance has been regarded as a necessary step to address the environmental repercussions of CO_2 emissions at the global level. A country can do this by putting money into renewable, climate-friendly energy sources. According to the report, a plan to prevent environmental degradation should incorporate renewable and ecologically friendly energy sectors. The electrical sector is likely to see increased investments and the implementation of new technology, both of which are positive developments. This will allow for the commercial and personal use of clean energy in both developed and developing countries. Thus, environmental harm is minimized, and economic expansion in countries is constrained. As a result, future initiatives should boost awareness and promote investment in renewable energy sources. With almost 40% of the world's population, BRICS covers nearly 27% of the total earth's land. So the impact of these big emerging economies substantially affects all other parts of the planet earth. Considering their vital economic growth and expansion, authorities should view their energy policy to counteract environmental pollution e.g., CO_2 emission, which is the focus of this article. Thanks to geography, there are no landlocked countries in this domain that ensures vast coastal areas. Vast land covers countless crisscrossing rivers flowing from hills and mountains to the sea. Rough terrain and even deserts are prevalent in BRICS. It all means that setting up a nuclear, hydroelectric, solar panel, or larger windmill project should not be a big issue regarding space, security, scope, and overall viability. Therefore, BRICS countries must increase energy efficiency and engage in renewable energy research and development to reduce carbon emissions.

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