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The influence of institutional quality on environmental efficiency of energy consumption in BRICS countries

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It has been observed in the literature that efficient energy use reduces production cost and carbon emissions into the environment. This study further argues that institutional quality enhances environmental efficiency of energy consumption. Therefore, this study was carried out with the aim of exploring the influence of institutional quality on environmental efficiency of energy use in BRICS countries for the period from 2001 to 2020. A two-step procedure was carried out to achieve the objectives of this study. First, the environmental efficiency of energy consumption was estimated using the stochastic Frontier analysis (SFA) technique. The results of the SFA approach show that the average environmental efficiency of energy use in BRICS countries is 61%, ranging from 37.5 to 100%. Furthermore, there is 39% room for improvement in environmental efficiency of energy use in BRICS countries. Moreover, the SFA results also indicate that South Africa has the highest average environmental efficiency, and China has the lowest environmental efficiency score among BRICS countries. Second, this study employed the system GMM technique to explore the impact of institutional quality on environmental efficiency of energy consumption in BRICS countries. The results of the system GMM show that institutional quality plays a significant role in improving environmental efficiency of energy consumption in BRICS countries. Finally, this study recommends some policy measures based on the study's findings to improve environmental efficiency of energy consumption.

KEYWORDS

environmental efficiency, institutional quality, SFA approach, system GMM, BRICS countries

1 Introduction

Labor and capital are considered the engine of economic growth by neoclassical economists, but nowadays energy is considered an important input and core element of economic growth. Therefore, economic growth of a country relies on its energy input (Zheng and Walsh, 2019; Pehlivanoglu et al., 2021). But energy use is considered the main source of GHG (greenhouse gas) emissions. According to the WHO (2021), 85% of CO_2

emissions are caused by primary energy consumption. Moreover, the findings of Lorente et al. (2022) also confirmed positive relation between carbon dioxide (CO_2) emission and energy consumption. The study of Dogan et al. (2022) also found positive and significant impact of energy consumption on carbon dioxide (CO_2) emissions. Usman et al. (2022) found that non-renewable energy consumption causes degradation of environment and one percent increase in non-renewable energy use increases carbon dioxide emission by 0.71 percent. CO_2 emission negatively affects humans including animal species and about 7 million people per year die due to the adverse effect of CO_2 emission (World Health Organization, 2021). CO_2 emission also causes significant climate change and global warming (Usman and Balsalobre-Lorente, 2022). Therefore, energy consumption is also considered a source of negative externalities and environmental degradation. Efficient energy use is considered a solution to negative externalities (Filippini and Zhang, 2016). The efficient use of energy is the important policy strategy for GHG emissions (IEA, 2009). Some studies also explored that the efficient use policy is a GHG reduction solution, as the study by Trianni et al. (2016) found that improving efficiency in industries is the best tool for reducing GHG emissions. In addition, efficient energy use will also lower production cost. The findings of Sinha et al. (2022) also demonstrated that efficient use of energy improves skills of labor to utilize capital more efficiently and consequently contributes to production system.

Efficient use of energy causes GHG emissions to decline, therefore, governments in many countries have developed policies for efficient energy use (IEA, 2014). For example, policies for the production and use of renewable energy, commercialization of energy technology, control of energy intensity and energy transition. These policies are implemented by government institutions. These government institutions have strong political, constitutional and governmental power. Therefore, these institutions are considered resourceful in the application of government policies in relation to energy efficiency (Vowles, 2008). The effective implementation of energy policies by government institutions ultimately determines consumers' energy consumption behavior (Chang et al., 2018). However, the effective execution of these policies depends on institutional quality (Bhattacharya et al., 2017; Chang et al., 2018). Therefore, improving efficiency is an institutional quality issue, and institutional quality plays a vital role in efficient energy use.

Environmental efficiency referred to the ratio between minimum viable use and the actual use of harmful input. In other words, environmental efficiency is reduction of harmful input to minimum viable level from the observed level, keeping both the output and normal inputs constant (Reinhard et al., 1999; Reinhard and Thijssen, 2000). Therefore, environmental efficiency of energy consumption is ratio of the least viable energy use to the actual energy use. Previous studies estimated environmental efficiency through the TFEE (total factor energy efficiency). In the case of input-oriented, the TFEE is reduction of good and bad inputs without reducing observed production from its initial level and in the case of output-oriented the TFEE is increasing level of production without increasing level of inputs (Otsuka & Goto, 2015; Proskuryakova and Kovalev, 2015; Sun et al., 2019; Cai et al., 2020). Song et al. (2015) estimated total environmental efficiency of transport sector considering both normal and harmful inputs and outputs.

This study has two objectives. First, to compute environmental efficiency of energy use in the BRICS countries and, the second objective is to explore the impact of institutional quality on environmental efficiency of energy use. A novel aspect of this study is the computation of the environmental efficiency of the harmful input (energy) at a macro level, different from previous studies where the focus was to compute total factor energy efficiency. This study is also novel in relation to its second objective, that is, the impact of institutional quality on environmental efficiency of energy consumption. Some studies have analyzed the impact of institutional quality on energy use efficiency. Sun et al. (2019) investigated effect of institutional quality on total factor energy efficiency (TFEE). But, as far as this study in concerned, no work has been done on the impact of institutional quality on the environmental efficiency of energy consumption. The findings of this study will also serve as policy guidelines for policymakers as they frame policies related to efficient energy use. BRICS countries were selected for this study for different reasons: (1). The BRICS countries are on the list of the biggest emitters of CO_2 and face the problem of climate change. CO_2 emission has been increasing over time in BRICS countries. (2). Energy consumption has also been increasing over time due to high investment in industry and infrastructure. BRICS countries are among the twenty largest energy consumers. China leads the list with energy consumption of 123.591 QBTU, and only two sectors i.e., power and heating sector consume 50 percent of China total energy consumption (Jiang et al., 2022). Russia is in 3rd position with energy consumption of 64.278 QBTU, India is in 7th position with energy consumption of 17.785 QBTU, Brazil is in 10th place with energy consumption of 12.713 QBTU and South Africa is in the 19th position with energy consumption of 5.913 QBTU (USEIA, 2021). Three BRICS countries are among the biggest electricity consumers in the world. China leads the list with electricity consumption of 5.934 trillion kilowatt-hours, India is in 3rd position with electricity consumption of 1.176 kilowatt-hours and Russia is in 5th position with electricity consumption of 918.58 billion kilowatts-hour. China also leads the list of greenhouse gas emitters in the world. China emits 9,300 million tons, India is in 3rd position emitting 2,200 million tons, Russia is in 4th position emitting 1,500 million tons, Brazil is in 13th position emitting

427.6 million tons and South Africa is in the 14th position emitting 421.7 million tons (World Population Review, 2022).

The contribution of this study in view of the above discussion is fourfold: first, previous studies have focused on total factor energy efficiency, ignoring its detrimental impact. Energy consumption has harmful effects along with its role in production, such as GHGs emissions. In addition, excessive energy use causes an increase in energy demand, energy price and, consequently, increases the total cost of production. Therefore, this is the first study to calculate the environmental efficiency of energy consumption in BRICS region. Second, previous studies explored the effect of institutional quality on the total factor energy efficiency, ignoring its impact on the environmental efficiency of energy use. Institutions play a significant role in the implementation of energy policies and efficient energy consumption, consequently, leading to an improvement in the environmental efficiency of energy utilization. Third, this study is also new in terms of exploring the effect of human capital, trade openness and industrial size on the environmental efficiency of energy consumption. Finally, this study recommends some policy implications to improve environmental efficiency of energy consumption based on research findings. The rest of the article is outlined as bellows: section 2 elaborates the literature review directly or indirectly related to this study. The methodology of the study was explained in section 3. The results and discussion were discussed in section 4. The conclusions and recommendations were deduced in section 5. This section was followed by the references of the study.

2 Literature review

This section reviewed previous studies directly or indirectly related to this study. First, the study reviewed two approaches widely used to compute efficiency. Second, the study reviewed studies that estimated the efficiency of different sectors using these approaches. Finally, the study reviewed studies that explored the effect of institutional qualities on energy use efficiency/environmental efficiency of energy utilization.

2.1 Literature review on efficiency estimation

The two basic methods for energy efficiency estimation are DEA (data envelopment analysis) and SFA (stochastic Frontier analysis). DEA is based on mathematical programming and SFA is based on the econometric technique. DEA is a useful technique for estimating efficiency used by many studies. Ibrahim et al. (2021) used DEA to compute efficiency of the social ecological system and Lu et al. (2019) estimated economic-environmental efficiency of energy using DEA and Wang and Wang (2020) calculated energy efficiency using DEA. This approach has some shortcomings. It considers stochastic error terms as part of efficiency elements and causes efficiency estimates to be biased. It has no assumptions about model's functional form and is therefore unable to handle measurement errors in the data. Furthermore, It does not separate statistical noise from inefficiency Wang and Sun (2020) discussed the disadvantage of traditional DEA in their study and stated that traditional DEA does not consider the inhomogeneity of DMUs. Wang et al. (2018) and Wang et al. (2021a) used Fussy DEA, but this method is suitable for large sample datasets. Stochastic Frontier analysis (SFA) developed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), has been widely used for efficiency estimation at both micro and macro levels. The SFA requires selection of appropriate functional form and therefore can handle measurement errors in the data. The SFA also separately identifies statistical noise and inefficiency. Therefore, this paper employed the SFA technique to estimate environmental efficiency of energy consumption in BRICS countries.

Data envelopment analysis (DEA) and stochastic Frontier analysis (SFA) are two different techniques employed by previous studies to compute energy efficiency of different sectors. Lu et al. (2019) calculated total factor environmental efficiency and energy consumption economic efficiency of 31 Chinese provinces using DEA approach. The results revealed positive association between economic and environmental efficiency and an increasing trend towards economic and environmental efficiency was also found. Song et al. (2016) estimated environmental efficiency of energy use in road transport using a super efficiency slack-based method. Results indicate that environmental efficiency is not optimal and there are differences between regions in terms of environmental efficiency. Iram et al. (2020) used DEA to compute environmental efficiency for OECD countries by including undesirable production in the efficiency model. The results indicate that Hong Kong, Singapore, Brunei and Australia are the most efficient countries regarding energy efficiency and CO_2 emission reduction. Bibi et al. (2021) calculated technical and environmental efficiency of energy use in rural South Asia employing SFA. Findings indicate that technical efficiency can be eliminated by increasing agricultural production by 8%. The paper also explored that environmental efficiency could increase by 23%. Võ and Yabe (2015) calculated the technical and environmental efficiency of rice production in the Mekong Delta in Vietnam. They used the SFA approach, and the result found that the environmental efficiency of ecological rice and normal rice is 85.54 and 84.54% respectively, and technical efficiency of both is 92.24 and 92.17%, respectively. Chaudhuri (2016) estimated the technical efficiency of Indian electronics companies for the period 2002–2010 and found downward technical efficiency. Filippini & Hunt (2016) used Mundlak (1978) method to compute aggregate energy efficiency in the US. Hsiao et al. (2018) computed TFEE using SFA of

10 Baltic Sea economies and found an upward trend of average energy use efficiency score over the period 2004 to 2014 and found that Norway, Sweden, Finland and Latvia have high efficiency score than other economies in the Baltic Sea region. Zhang et al. (2011) computed TFEE of 23 emerging economies for the period 1980 to 2005 and found a decreasing trend in TFEE. Filippini & Hunt (2011) computed aggregate energy demand and energy use efficiency for 29 OECD economies employing SFA. Zhou et al. (2012) used shepherd energy distance function to calculate energy use efficiency for a sample of OECD economies. Alsahlawi (2013) calculated energy efficiency for Gulf Cooperation Council (GCC) economies using DEA approach. They estimated two models; in the first model, only energy was incorporated as an input and in the second model, other inputs were incorporated with the energy input in the energy efficiency model. The results show that Kuwait is efficient according to both models, UEA, Oman and Bahrain were considered inefficient by both models and Saudi Arabia and Qatar are efficient according to model 2 and inefficient according to model 1.

2.2 Literature review on energy efficiency and its determinants

Previous studies related to the second objective of this study are reviewed here. Sun et al. (2019) investigated effects of institutional quality on energy efficiency of 71 developing and developed economies. Their results reveal a positive and significant influence of institutional quality on energy efficiency. Sun et al. (2021) studied effects of the institutional quality of neighboring region on domestic energy efficiency in a panel of 99 regions. Results of the study indicate that institutions in neighboring countries have significant and positive influence on the energy efficiency of domestic countries. Du et al. (2016) studied effects of institutional quality on productivity and energy efficiency and found that institutional quality improves energy efficiency and productivity in China. Chang et al. (2018) examined the nexus between energy efficiency and government efficiency and explored a positive effect of government efficiency on energy efficiency. Zhang & Huang (2017) explored government role in energy savings and found an effective government role in energy savings in OECD economies. Chou et al. (2020) explored a positive effect of democratic institutions on energy efficiency.

In view of the above discussion; First, it is revealed that no research was carried out to calculate the environmental efficiency of energy as a harmful input. Second, no studies were carried out in the past to assess the influence of institutional quality on the environmental efficiency of energy consumption. Therefore, this study fills the gap to compute the environmental efficiency of energy as a harmful input rather than the TFEE (total factor energy efficiency), and then investigates the effects of institutional quality on environmental efficiency of energy use in BRICS countries.

3 Methodology

This study explores two core objectives: first, to compute environmental efficiency of energy use in BRICS countries for the period 2001 to 2020; second motive to assess the influence of institutional quality on environmental efficiency of energy consumption in BRICS countries. Data on dependent and independent variables were collected from different sources including the World Bank (World Bank, 2021), International Labor Organization (ILO, 2021) and the US Energy Information Administration (USEIA, 2021).

First, this study estimated energy efficiency using SFA devised by Aigner et al. (1977). Khan and Ullah (2020) also used SFA to estimate technical and environmental efficiency of rural Southeast Asia. Honma and Hu (2014) used this method to calculate energy efficiency in Japanese region. Zhou et al. (2012) also transformed the Shepard distance function into a SFA model for calculating energy efficiency. In this research, TFEE is used as a measure of energy efficiency. The TFEE value ranges from zero to one. TFEE value close to one show that the country is more efficient in energy use and the value close to zero shows that the country is less efficient, that is, energy is used more inefficiently. The stochastic Frontier analysis considers labor, capital and energy consumption as inputs and the Gross Domestic Product (GDP), based on constant 2015 US dollars, as output. To estimate the energy efficiency, GDP was used as the dependent factor and labor, capital and energy use were taken as independent factors. Labor and capital were donated by X and energy consumption was denoted by D in the energy efficiency estimation model. Energy consumption was denoted by a separate variable due to its harmful environmental effects. An improvement in energy efficiency causes a decline in energy consumption. Table 1 presents a detailed variables' description. This study computes the environmental efficiency of the harmful input only and energy consumption was considered the harmful input. Therefore, the environmental efficiency of energy use is referred to the ratio of the least viable energy use to the actual energy use. The environmental efficiency of energy consumption was derived from the TFEE (total factor energy efficiency). Therefore, energy efficiency improvement (TFEE) will cause improvement in the environmental efficiency of energy utilization. The technical efficiency of any country will necessarily result in the environmental efficiency of energy consumption. Therefore, any factor that improves the technical efficiency of energy consumption will also increase the environmental efficiency of energy consumption.

Second, the generalized method of momentum (GMM) approach was employed to examine achieve second objective of this study; to analyze influence of institutional quality on

TABLE 1 Explanation of variables and data sources.

The stochastic frontier analysis (SFA) approach

Variables	Abbreviation	Units	Source
Output	Y	Gross Domestic product measured in constant 2015 billion US dollars was use as a proxy for output	World Bank (2021)
Capital	K	Gross capital formation based on 2015 constant billion US dollar was used as a measure of capital	World Bank (2021)
Labor	L	Total employment measured in millions of people	ILO (2021)
Energy consumption	E	Total energy consumption measured in Quadrillion British thermal unit (QDBTU)	US Energy Information Administration USEIA, (2021)
The generalized method of movement (GMM) approach			
Environmental efficiency of energy consumption	EE	Measured as a percentage and estimated using the SFA	Authors' calculation
Institutional quality	IQ	Index	World Bank (2021)
Human capital	HC	Index	Pen World Table (2021)
Trade openness	TO	Measured as the ratio of exports plus imports to GDP	World Bank (2021)
Industrial size	IS	Measured as the ratio of industrial value added to GDP	World Bank (2021)

environmental efficiency of energy consumption. In the GMM model, environmental energy efficiency was used as a dependent variable and institutional quality (IQ), Human Capital (HC), Trade Openness (TO) and Industrial Size (IS) were used as independent variables.

3.1 Selection of variables

The reasons behind incorporating these variables into the GMM are explained below:

3.1.1 Institutional quality

Institutional quality affects environmental efficiency of energy use through technical efficiency of energy use. Institutional quality causes a decrease in energy use because efficient institutions have strong constitutional and political influences in implementing energy policies effectively and regulating the energy consumption attitude of all energy users (Vowels, 2008). Effective implementation of energy policies leads to reduced energy consumption and improved energy efficiency. Burke and Stephen (2018) stated that the energy sector needs efficient management, infrastructure and direction, which makes an institutional quality that affects energy efficiency. Furthermore, Wang et al. (2021b) stated that strict regulation leads to resource efficiency. Strict regulation can be implemented by efficient institutions. Therefore, Wang et al. (2019) also corroborate the positive relationship between environmental energy efficiency and institutional quality. Any improvement in technical energy efficiency will necessarily increase environmental efficiency of energy consumption so, institutional quality affects environmental efficiency of energy use. Most previous studies have found positive influence of institutional quality on energy efficiency; therefore, institutional quality will have positive influence on the environmental efficiency of energy consumption. The institutional quality index was derived from the World Economic Freedom Index. This index was utilized to measure the institutional quality standard (Young and Sheehan, 2014). This index was constructed using five other indices: legal system, government size, financial health, business regulation, and trade liberalization.

3.1.2 Human capital

It has positive effects on environmental efficiency of energy consumption. Two different views explain the positive relation between environmental efficiency of energy use and human capital. First view demonstrated by the recent literature on human capital shows that the advance in human capital causes a decline in the use of non-renewable energy (Alvarado et al., 2021). A decrease in non-renewable energy use consequently causes a decline in air, water and soil pollution (Fang & Chen, 2017). Therefore, increasing human capital will reduce pollution per unit of energy use and increase environmental efficiency of energy consumption. Human capital also improves environmental sustainability (Jahanger et al., 2022). The second view demonstrates that human capital improves environmental efficiency through its impact on technical efficiency. The human capital formation allows the country to use energy-efficient technology, reducing energy use (Li and Lin, 2016). As improving technical efficiency will necessarily improve environmental efficiency, therefore, increasing human capital improves the environmental efficiency of energy utilization. The human capital index was calculated by the Penn World Table based on average years of schooling and return to education.

3.1.3 Trade openness

The degree of trade openness of a country determines technological spillover. It is considered vital for technology diffusion. Technological spillover and diffusion consequently increase the total energy efficiency of the factor (Cei at al., 2017). Improving energy efficiency leads to improved environmental energy efficiency. Therefore, trade opening is expected to improve environmental efficiency. The existing literature also supports the negative effects of free trade on energy efficiency. In recent decades, free trade has enhanced energy use and carbon dioxide (CO_2)emissions. Therefore, the intensification of energy use and carbon dioxide emissions cause a decline in both TFEE (total factor energy efficiency) and environmental efficiency of energy consumption.

3.1.4 Industrial size

Energy is used efficiently in the industrial sector due to a few reasons: industrial agglomeration under economies of scale results in efficiency in energy use (Sun et al., 2011), decrease in cost of energy efficiency technology (Jardot et al., 2010) and increased productivity due to the efficient use of equipment (Wang and Wang, 2020). Therefore, an increase in the size of the industry due to the mentioned reasons improves the energy efficiency and environmental efficiency of energy consumption (Khan & Ullah, 2019).

3.2 Econometric model

First, this study employed SFA using the Cobb-Douglas production function to estimate the TFEE:

$$ln\,Y_{it} = \alpha_0 + a_j\,ln\,X_{it} + \beta_k\,ln\,D_{it} + V_{it} - U_i \quad (1)$$

In eq. 1, Y denotes output, X represents labor and capital, D_{it} denotes environmentally harmful input (energy consumption), V_{it} is random error term assumed to be white noise. U_i measures TFEE which is a non-negative stochastic variable and is also assumed to be white noise. Before estimating Eq. 1, the likelihood ratio test was used to select the appropriate functional form of the SFA. Following likelihood ratio was calculated:

$$\lambda = -2\{ln[L(H_0)] - ln[L(H_1)]\} \quad (2)$$

Where λ denotes the likelihood ratio and $ln[L(H_0)]$ calculates logarithm of the likelihood ratio of the Cobb-Douglas model. H_0 undertakes that the Cobb-Douglas is the appropriate functional form. $ln[L(H_1)]$ calculates the log likelihood ratio value of the translog model, that is, H_1 undertakes that translog is the appropriate model. This test follows the chi-square distribution (Coelli et al., 1998). Likelihood test was used to verify presence of inefficiency in energy use. The likelihood test expressed as $\gamma = \sigma_u^2/\sigma^2$; where σ^2 is equal to σ_u^2 plusσ_v^2. The null hypothesis of the log-likelihood test states that there is no inefficiency in the energy use and the alternative hypothesis is stated that the inefficiency exists in the energy use. The study specified the following Cobb-Douglas stochastic Frontier approach:

$$ln\,Y_{it} = \alpha_0 + \alpha_1\,ln\,K_{it} + \alpha_2\,ln\,L_{it} + \alpha_3 E_{it} + V_{it} - U_i \quad (3)$$

Where K_{it} denotes capital, L_{it} denotes total labor employed and E_{it} is energy consumption which is considered harmful input. After estimating Eq. 3, the TFEE for each country was estimated using Eq. 4:

$$TFEE_c^t = \exp\left(-u_c^t\right) \quad (4)$$

Environmental efficiency (EE) is the only aspect of the TFEE, as the EE only calculates the possible decrease in harmful inputs, while the input oriented TFEE considers the reduction in all inputs, including normal inputs and harmful inputs. A technically efficient country is necessarily environmentally efficient and, therefore, Reinhard et al. (1999) and Reinhard et al. (2000) suggested setting $U_i$equal to zero in Eq. 3 and substituting all harmful inputs E_m with $\varnothing E_m$ where ∅ denotes environmental efficiency (EE) score. Following the suggestions of (Reinhard et al., 1999; Reinhard et al., 2000), we obtained the following equation:

$$ln\,Y_{it} = \alpha_0 + \alpha_1\,ln\,K_{it} + \alpha_2\,ln\,L_{it} + \alpha_3 Ln\,\varnothing E_{it} + V_{it} - U_i \quad (5)$$

The definition of EE implies that the output in Eq. 5 is equal to the output in the Eq. 3. Therefore, setting Eq. 5 equal to Eq. 3 gives the following equation:

$$\alpha_m\,ln\,\varnothing E_m - a_m\,ln\,E_m + u_i = 0 \quad (6)$$

As $ln\,\varnothing_i = ln\,\varnothing_i E_m - ln\,E_m = ln\left(\frac{\varnothing_i E_m}{E_m}\right) = ln\,EE_i$

After some manipulation of Eq. 6, we got the following equation:

$$ln\,EE_i + U_i = 0$$
$$EE_i = antilog\,(-U_i) \quad (7)$$

EE_i in Eq. 7 calculates the environmental efficiency of each country.

Finally, GMM proposed by Blundell and Bond (1998) and Arellano and Bover (1995) was used to assess the influence of institutional quality on environmental efficiency of energy use in BRICS countries. The econometric model may have endogeneity problem, that is, the correlation between independent factors and residuals. Bond (2002) states that OLS in presence of an endogeneity problem, produces a maximum estimate with an upward bias and a fixed effect produces a maximum estimate with a downward bias; therefore, the GMM approach solves the endogeneity problem. This technique analyzes the relationship between dependent and independent variables in a dynamic

TABLE 2 Descriptive statistics of the variables.

The stochastic frontier analysis (SFA) approach

Variables	Brazil	Russia	India	China	South Africa
GDP					
Mean	1,610	1,230	1,660	8,230	308
S. Dev	229	201	609	3,850	42.9
Max	1870	1,460	2,700	14,600	359
Min	1,200	820	839	3,000	228
Capital					
Mean	281	299	534	3,430	53
S. Dev	58.20	65	1830	1830	10.8
Max	381	398	871	6,370	64.6
Min	195	195	180	841	29.9
Labor					
Mean	84.08	69.02	14.50	718.17	14.50
S. Dev	5.90	2.23	1.71	166.92	1.71
Max	90.48	71.45	16.77	771.28	16.77
Min	70.48	2.23	11.44	11.65	11.44
Energy					
Mean	11.01	30.31	22.24	100.6	5.47
S. Dev	1.66	2.22	6.64	41.57	0.29
Max	12.81	33.85	32.37	151.61	5.8
Min	8.31	26.80	12.42	4.57	4.57
The generalized method of movement (GMM) approach					
Efficiency					
Mean	0.69	0.51	0.54	0.38	0.91
Max	0.76	0.52	0.63	0.48	1
Min	0.64	0.50	0.48	0.35	0.88
S. Dev. Quality Index	0.04	0.004	0.05	0.03	0.03
Mean	6.47	6.36	6.44	6.09	6.9
Max	6.75	6.9	6.68	6.54	7.01
Min	5.81	6.17	5.57	5.57	6.69
S. Dev	0.23	0.44	0.32	0.317	0.09
Human Capital Index					
Mean	2.57	3.31	1.98	2.5	2.53
Max	3.16	3.43	2.17	2.72	2.96
Min	2.09	3.18	1.80	2.33	2.12
S. Dev	0.34	0.08	0.12	0.13	0.26
Trade Openness					
Mean	210	386	379.23	1,460	88.6
Max	347	469	639	2,560	124
Min	68.3	74.30	65.2	244	30.9
S. Dev	93.3	121	193	795	29
Industrial Size					
Mean	0.21	0.06	0.27	0.39	0.25
Max	0.22	0.09	0.29	0.41	0.28
Min	0.18	0.029	0.25	0.37	0.21
S. Dev	0.22	0.021	0.01	0.126	0.02

Source: Authors' Calculation.

panel model. The model based on the GMM approach is free of autocorrelation and heteroscedasticity problems and produces consistent and more adequate results even in the presence of heteroscedasticity. It also controls for unobserved heterogeneity. The GMM approach used in this study was expressed using the following model:

$$ln\,EE_{it} = \beta_0 + \beta_1\, lnEE_{it-1} + \beta_2\, Ln\,IQ_{it} + \beta_3\, Ln\,HC_{it} + \beta_4\, Ln\,TO_{it} + \beta_5\, Ln\,IS_{it} + Z_i + \varepsilon_{it} \tag{8}$$

Where, the subscripts t and i denote time and country respectively, EE_{it-1}denotes lagged term of each country's environmental energy efficiency, β_s are the slope coefficients of each independent variable, z denotes country-specific effect, and ε error term and both are individualistically, and identically scattered with zero mean and persistent variance that is, ($z_i \approx iid\,(0,\, \delta_z^2)\, and\, \epsilon_{it} \approx (0,\, \delta_\varepsilon^2)$.

To obtain a consistent estimator of GMM, it must pass the Hansen test. This test verifies the overidentification and autocorrelation constraints in the model's error term. The Hansen test (2005) was employed to prove correct specification of model or to assess the general rationality of the instruments. Therefore, null hypothesis of the Hansen test shows no correlation between instruments and residual. Acceptance of the null hypothesis leads to the conclusion that the instruments are valid, meaning that these instruments have no correlation with residual. In the case of the serial correlation test, there are two null hypotheses: first null hypothesis is no first order serial correlation, i.e., AR (1) and second null hypothesis is no second order serial correlation. To find consistent GMM estimators, the first null hypothesis must be rejected, and the second null hypothesis must be accepted. Furthermore, the multicollinearity problem in the GMM was verified using the VIF (variance inflation factor). VIF larger than 10, shows that the factor is highly collinear with another independent variable. (Gujarati, 2003). The system GMM has some advantages over other panel data techniques. First, other panel data techniques produce inconsistent and biased estimates in presence of a lagged dependent factor and endogeneity problem caused by regressors (Harris and Mátyás, 2004). Second, the GMM system produces consistent and efficient estimates even in the presence of autocorrelation and heteroscedasticity. Furthermore, the system GMM is also ideal over the difference GMM in case of unbalanced panel data (Roodman, 2009).

4 Results and discussions

Descriptive states demonstrate some basic features of the data series. Table 2 shows so characteristics of the data series used in estimating the SFA model. The SFA approach was employed to calculate the environmental efficiency of energy consumption in BRICS countries. Four variables were used in the estimation of environmental energy efficiency. The table indicates that China has the highest average GDP of USD 8230 billion, followed by India, Brazil, Russia and South Africa. Average GDPs of India, Brazil, Russia and South Africa are 1,660, 1,610, 1,230 and 308 billion US dollars, respectively. The same pattern was also observed in gross capital formation. The average capitals of China, India, Russia, Brazil and South Africa are 3,430, 534, 299, 281 and 53 billion US dollars, respectively. China has the highest overall employment during the sample period, followed by Brazil, Russia, India and South Africa. In the case of energy consumption, China is the main energy consumer followed by Russia, India, Brazil and South Africa. The average energy consumption of China, Russia, India and South Africa is 100.60, 30.31, 22.24, 11.01 and 5.47 quadrillion British thermal units, respectively. In addition, Table 2 also shows summary states of the data series employed in computation of GMM approach. South Africa has the highest average environmental efficiency (0.91). The mean environmental efficiency value of Brazil, Russia, India, China and South Africa was 0.69, 0.51, 0.54, 0.38 and 0.91, respectively. The average environmental efficiency of BRICS countries during sampled period was estimated 0.61 or 61 percent which indicates that 39 percent reduction is possible in energy consumption without affecting total production. The mean value of the intuitional quality index of Brazil, Russia, India, China and South Africa are 6.47, 6.36, 6.44, 6.11 and 6.9, respectively. Russia has the highest average value of human capital in the sampled period followed by Brazil, South Africa, China and India. The average human capital index value of Brazil, Russia, India, China and South Africa was estimated 2.57, 3.31, 1.98, 2.5 and 2.53, respectively. China has the highest average value of trade openness. The average values of trade openness for Brazil, Russia, India, China and South Africa are 210, 386, 379.23, 1,460, 88.6, respectively. China has the highest average industrial size value. The mean industrial size value of Brazil, Russia, India, China and South Africa was 0.21, 0.06, 0.27, 0.39 and 0.25, respectively.

The core objectives of the research are twofold: first, to calculate environmental efficiency of energy use and second, to assess the influence of institutional quality on environmental efficiency of energy use in BRICS countries. First, the environmental efficiency of energy consumption of BRICS countries was estimated using SFA approach. There are two commonly used functional forms of SFA approach, namely Cobb-Douglas and translog production functions. The likelihood ratio test was used to select appropriate functional form of SFA model. Null hypothesis is that the Cobb-Douglas functional form is the most suitable compared to the alternative hypothesis that the translog is the most suitable functional form. The p-value of likelihood ratio test is larger than 0.05, therefore, the null hypothesis is accepted, and it is concluded that the Cobb-Douglas is the appropriate functional form of SFA approach. The

TABLE 3 Outcomes of maximum likelihood random effect time-varying efficiency decay model.

Variables	Parameters	Coefficients	Standard errors	Probability
Constant	α_0	25.93	4.16	<0.01
Ln(K)	α_1	0.66*	0.02	<0.01
Ln(L)	α_2	-0.65*	0.16	<0.01
Ln(E)	α_3	0.07***	0.04	<0.10
ln(Sigma squared)	$ln\,\sigma^2$	0.11	0.11	0.88
Sigma squared	σ^2	1.12	0.82	
Gamma	Γ	0.99	0.001	
Sigma (σ_u^2)	σ_u^2	1.12	0.82	
Sigma (σ_v^2)	σ_v^2	0.002	0.0003	
Mu	μ	7.99	4.63	0.08
Eta	η	0.002	0.001	0.07
Log-likelihood	LL	147.39		<0.01

* and *** denote 1 percent and 10 percent significance levels.

TABLE 4 Environmental Efficiency score of energy consumption in BRICS countries.

Years	Brazil	Russia	India	China	South Africa	Average
2001	0.76	0.51	0.63	0.44	1	0.67
2002	0.76	0.51	0.62	0.43	0.98	0.66
2003	0.75	0.51	0.62	0.42	0.95	0.65
2004	0.74	0.50	0.60	0.40	0.94	0.64
2005	0.73	0.51	0.59	0.39	0.93	0.63
2006	0.72	0.50	0.57	0.39	0.93	0.62
2007	0.70	0.51	0.56	0.38	0.91	0.61
2008	0.69	0.50	0.55	0.38	0.91	0.61
2009	0.70	0.52	0.54	0.37	0.91	0.61
2010	0.67	0.50	0.53	0.37	0.89	0.6
2011	0.66	0.51	0.52	0.36	0.91	0.6
2012	0.66	0.50	0.51	0.36	0.89	0.59
2013	0.65	0.50	0.51	0.35	0.89	0.58
2014	0.64	0.50	0.50	0.35	0.90	0.58
2015	0.65	0.51	0.50	0.36	0.90	0.58
2016	0.65	0.51	0.50	0.36	0.90	0.58
2017	0.65	0.51	0.49	0.35	0.89	0.58
2018	0.65	0.50	0.48	0.35	0.91	0.58
2019	0.65	0.50	0.48	0.35	0.89	0.57
2020	0.65	0.50	0.48	0.35	0.88	0.57
Average	0.69	0.51	0.54	0.38	0.91	0.61
Rank	2	4	3	5	1	

Source: Authors' Calculation.

existence and absence of energy inefficiency was verified by the log-likelihood test (Coelli et al., 1998). The result of the Log-likelihood test shows the presence of energy inefficiency, as the calculated value of the Log-likelihood test is 147.39, which is bigger than the tabularized value. The gamma (γ) value in Table 3 measures the variation in total production due to technical efficiency. A gamma (γ) value close to one demonstrates that SFA is the most suitable model. In this study, the gamma value is

TABLE 5 Results of the system GMM approach.

Variables	Parameters	Values	St. Error	Prob
$lnEE_{t-1}$	β_1	0.96*	0.010	<0.01
lnIQ	β_2	0.10*	0.030	<0.01
lnHC	β_3	0.04*	0.007	<0.01
lnTO	β_4	-0.001*	0.002	<0.01
lnIS	β_5	0.006**	0.002	<0.05
Diagnostic Statistics				
No of observations		100		
No of groups		5		
Hansen Test (prob-value.)		0.075		
AR (1): *p*-value		<0.01		
AR (2): *p*-value		0.859		

* and ** denote 1 percent and 5 percent significance level.

0.99, which shows that the SFA is the best model, and indicates that the 99% variation in total production is caused by technical inefficiency. Gamma is equal to σ_u^2/σ^2 where σ^2 is equals to σ_u^2 plusσ_v^2. Table 3 gives the findings of Equation 3 estimated using the ML random effect time-varying efficiency decay model (Battese and Coelli, 1992).

Table 4 presents the environmental efficiency score of energy use in BRICS countries. The last column shows the average environmental efficiency of energy utilization of each country during the sampled period. The average environmental efficiency score for Brazil, Russia, India, China and South Africa was estimated 0.69, 0.51, 0.54, 0.38 and 0.91, respectively. South Africa has the highest environmental efficiency scores, followed by Brazil, India, Russia and China. Russia ranks 4th in terms of environmental efficiency and is the second largest energy consumer among BRICS countries. South Africa ranks last in terms of energy users but has the highest environmental efficiency score among BRICS countries. The results of this study reveal that energy consumption and environmental efficiency scores go in opposite directions. The average efficiency of BRICS countries during the sampled period is 61%, which shows that energy consumption can be reduced by 40% without affecting total production.

Before using the GMM approach, this study employed the VIF (variance inflation factor) test to calculate the correlation between the regressors and ensure that there is no serious multicollinearity problem. VIF value for institutional quality, human capital, trade openness and industrial size are 1.06, 3.03, 2.49 and 4.55, respectively. VIF values of all independent factors range from 1 to 4.55 which indicate moderate correlation between the independent factors, but this moderate correlation does not need to be addressed (Khan et al., 2022). Therefore, it is concluded that the model does not have a multicollinearity problem. Finally, GMM model was assess the influence of institutional quality on environmental efficiency of energy use in BRICS countries. Results of GMM approach are presented in Table 5. The result confirms the consistency assumption of the GMM model, as null hypothesis of Hansen test (Hansen, 2005) is rejected, and rationality of the instruments was confirmed. Hansen test also confirms presence of first-order serial correlation AR (1) and absence of second-order serial correlation AR (2). The coefficient of all variables is significant, and their signs came out as expected. As this study did not find any previous studies on estimating environmental efficiency of energy use and influence of institutional quality on environmental efficiency of energy consumption, few studies were found that investigated impacts of institutional quality on technical efficiency of energy use. Therefore, findings of this study are not directly comparable with previous studies, but findings are consistent with the results of past studies indirectly based on the notion that a technically efficient country must be environmentally efficient. Therefore, any factor that affects technical efficiency is likely to affect the environmental efficiency of energy use.

This study found positive and significant impact of institutional quality on environmental efficiency of energy use. The outcomes are consistent with findings of Sun et al. (2019) who carried out the study to find the effect of institutional quality and green innovation on technical energy efficiency. Moreover, institutional quality improves environmental efficiency due to its strong constitutional and political influences in executing government policies effectively (Vowels, 2008). Human capital coefficient is also positive and significant. These findings are indirectly consistent with the finding of Twum et al. (2021) who investigated the impact of human capital on the technical efficiency of energy use. Human capital may increase environmental efficiency by decreasing non-renewable energy consumption (Alvarado et al., 2021) and a reduction in non-renewable energy utilization causes reduction in water, soil and air pollution (Fang & Chen, 2017). The accumulation of human capital allows the country to neutralize new technologies, help in the efficient use of existing technology and reduce energy use. Therefore, human capital improves the environmental efficiency of energy consumption. The industrial size coefficient is positive, and this finding is consistent with the outcomes of Wang and Wang (2020) who explored the impacts of technological innovation on total factor energy efficiency (TFEE) and industrial structure was used as control variables. Industrial size enhances environmental efficiency due to few reasons: economies of scale improve energy efficiency (Sun et al., 2011), use of energy efficient technology (Jardot et al., 2010) and increase in productivity due to efficient use of equipment (Wang & Wang, 2020). The trade openness coefficient is negative; it increases emission of CO_2 and causes a decreases in environmental efficiency of energy consumption. In recent decades, free trade has increased energy consumption and CO_2 emissions. Therefore, trade openness causes decline in total factor energy efficiency (TFEE) and environmental efficiency of energy use. All variables were considered significant at the 1 percent level of significance. Trade openness is a major determinant of energy efficiency and was not found in the previous literature, but the negative effect of trade openness on the environmental efficiency of energy use is indirectly consistent with the finding of the previous study, as the existing literature demonstrates that trade openness causes a significant increase in energy consumption, so trade opening indirectly causes decline in total factor energy efficiency and environmental efficiency of energy use (Khan et al., 2021). *p*-value of the Hansen test is larger than 0.05. Probability value of AR (1) is fewer than 0.05 and the probability value of AR (2) is greater than 0.05. Therefore, two assumptions for consistency of GMM were satisfied, that is, rationality of the instruments and occurrence of first order serial correlation and nonappearance of second order serial correlation.

5 Conclusions and policy implications

The main objectives of this study are twofold: first, to estimate environmental efficiency of energy use in BRICS countries. Second to investigate the impact of institutional quality on environmental efficiency of energy use using balanced panel data for the period from 2001 to 2020. The findings of the SFA show presence of inefficiency. Results also indicate that average environmental efficiency of energy consumption is 61%, ranging from 35 to 100%.%. Moreover, there is 39% room for improvement in environmental efficiency of energy consumption in BRICS countries South Africa has the maximum average environmental efficiency score (91%) and China has the lowest average efficiency score (36%). The findings of the GMM approach reveal that institutional quality, human capital and industrial size have positive and significant effects on the environmental efficiency of energy consumption in BRICS countries, and trade openness has a negative effect on the environmental efficiency of energy consumption. Moreover, the findings indicate that institutional quality plays a significant role in improving environmental efficiency of energy consumption. Improving energy efficiency will save energy, minimize production cost and reduce greenhouse gas emissions. Finally, this study prescribes some policy measures based on the outcomes of the study to improve environmental efficiency of energy consumption in BRICS countries, and around the world. This study concludes that institutional quality is a major factor in improving the environmental efficiency of energy use. Therefore, efficient use of energy can be ensured by strengthening institutions. The government should also make public awareness of energy use and its adverse effects on the environment. Moreover, the government should strictly enforce environmental laws through strong government institutions.

5.1 Limitations and future research direction

First, technological innovation is considered an important factor of technical and environmental efficiency of energy consumption, but due to the unavailability of complete data from BRICS countries, this factor was not considered in this study. Second, such a study could be carried out in the future in developing countries to investigate the effect of institutional quality and other factors on the environmental efficiency of energy use. Finally, this study estimated the environmental efficiency of energy consumption and energy was considered as a harmful input, therefore, this study also provides a direction to calculate the environmental efficiency of other harmful inputs such as fertilizers, green manures and pesticides/insecticides used. in the agricultural sector.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: www.worldbank.org.

Author contributions

Conceptualization, NR and DK; methodology, NR, DK, and RM; software, NR and DK; validation, NR, DK, and RM.; formal analysis, NR and DK; investigation, DK and RM; resources, RM; data curation, NR, DK, and RM; writing original draft preparation, NR, DK, and RM; writing review and editing, NR and DK; visualization, DK and RM; supervision, DK and RM; project administration, DK and RM; funding acquisition, RM. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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