Politická ekonomie
2024, Volume 72 (2), Special Issue:
Achieving Energy Transition and Sustainable Development:
The Roles of Political Risk and Energy Technology Investments

PRAGUE UNIVERSITY OF ECONOMICS AND BUSINESS

Sustainable Growth through Green Electricity Transition and Environmental Regulations: Do Risks Associated with Corruption and Bureaucracy Matter?

Runguo Xu, Ugur Korkut Pata, Jiapeng Dai

Runguo Xu (e-mail: xrg96@yonsei.ac.kr): School of International Relations Yonsei University, Seoul, South Korea

Ugur Korkut Pata (e-mail: korkutpata@osmaniye.edu.tr): Faculty of Economics and Administrative Sciences, Department of Economics, Osmaniye Korkut Ata University, Osmaniye, Turkey, Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon

Jiapeng Dai (*corresponding author,* e-mail: dai2015@snnu.edu.cn): School of Business, UOW Malaysia University College, Shah Alam, Malaysia

Abstract

Electricity production strategies of countries rely on fossil fuel-based electricity generation. Environmental regulations (*ER*) are needed to shift to green electricity for achieving energy transition, but corruption and bureaucracy can influence *ER*, energy transition and ecological quality. Hence, this research considers two important constituents of country risks including corruption and bureaucracy in the model while understanding the connections between green electricity, *ER* and the load capacity factor (*LCF*) in BRICS from 1992 to 2018. The research chooses a recent proxy of ecological quality (*i.e.*, *LCF*), which effectively measures the ecological quality and indicates the possibility of sustainable growth by using biocapacity and ecological footprint figures. The results of the research disclose that green electricity Granger-causes and enhances the *LCF*, whereas controlling corruption and enhancing bureaucracy quality improves ecological quality. *ER* improves environmental quality and the load capacity curve (LCC) hypothesis also exists. Lastly, policy directions are discussed.

Keywords: Corruption control, green electricity, environmental regulations, energy transition, bureaucracy quality
JEL Classification: Q2, O13, P180, Q50

Citation: Xu, R., Pata, U. K., Dai, J.: Sustainable Growth through Green Electricity Transition and Environmental Regulations: Do Risks Associated with Corruption and Bureaucracy Matter? *Politická ekonomie*, 72 (2), Special Issue, 228–254, https://doi.org/10.18267/j.polek.1420

1. Introduction

The rising environmental degradation around the globe, which is linked with economic development, has intensified climate change, resulting in various extreme weather events, such as storms, floods, droughts and others. According to WMO (2021), the world has suffered from almost 11,000 extreme weather disasters over the period from 1971 to 2019, claiming over 2 million lives and causing 3.64 trillion USD in losses. Therefore, sustainable development has emerged as an imperative requisite for fostering survival and advancement, ensuring growth while safeguarding against resource depletion and environmental degradation. To realize a sustainable development pattern, Goal 13 of the Sustainable Development Goals (SDGs) presents the concept of climate control for controlling hazardous emissions and minimizing their devastating impacts (UN, 2021).

Environmental devastation is closely tied to the utilization of fossil fuels for achieving economic growth (*EG*) (Can and Ahmed, 2022). Electricity is a necessity in every sector of the economy, and its generation also requires the consumption of energy (Salahuddin *et al*., 2017). The electrification approaches adopted by the majority of countries predominantly hinge on fossil fuel-based electricity generation. Consequently, enhancing environmental quality necessitates a paradigm shift towards augmenting electricity production sourced from clean energy, concurrently mitigating the reliance on electricity derived from fossil fuels (Balsalobre-Lorente *et al*., 2018). However, green electricity (*GE*) generation is a major challenge considering that developing countries cannot yet fully meet the demands for electricity, and around one billion people around the world are deprived of electricity (Zubi *et al*., 2016). Keeping in view the importance of this issue, green electricity has been given a vital place in the sustainable development agenda by integrating it into SDG 7. Environmental regulations (*ER*) are also a vital tool to influence climate control as well as SDG 7. Environmental regulations can limit the overdependence on fossil energy, promote energy saving, stimulate the generation of green energy and mitigate negative externalities of development (Murshed *et al*., 2021). However, if ecological regulations are weak, the host countries may suffer from high pollution levels due to the promotion of dirty industries and technologies (Ahmed *et al*., 2022). Thus, environmental laws may not always be stringent enough to control pollution levels in a country. This work examines the influences of *GE* and economic growth on ecological quality while including corruption control (*CRC*) and bureaucracy quality (*BQ*).

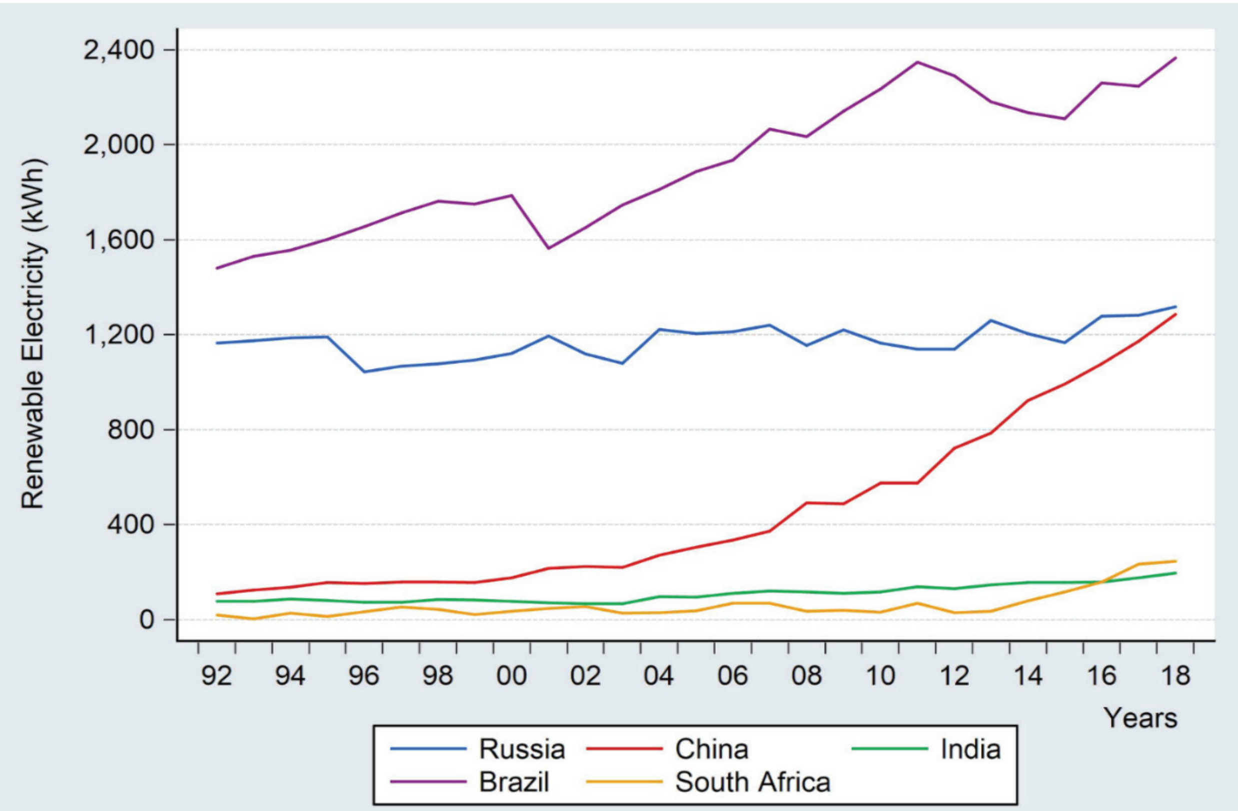
In the literature, studies have examined options and measures to reduce environmental deterioration by choosing various indicators for environmental quality and environmental degradation (Sinha *et al*., 2020). Among these, the ecological footprint (*EFP*) and CO_2 emissions are widely used indicators to gauge environmental deterioration. However, CO_2 cannot completely represent environmental deterioration, and it generally depicts the impacts of energy use (Al-Mulali *et al*., 2015). On the other hand, the comprehensive measure *EFP* only traces the impacts of human consumption through six different areas of land (Charfeddine, 2017), and overlooks the importance of the supply side. Indeed, biocapacity (*BC*) is an important indicator that represents this planet's ability to generate resources and assimilate waste, and excluding *BC* restricts the accurate valuation of environmental degradation (Shang *et al*., 2022). To address this issue, a new indicator can be computed by considering both *EFP* and *BC*; thus, Siche *et al*. (2010) recommended calculating the *LCF* (*BC* divided by *EFP*). The *LCF* depicts the extent to which the consumption needs of a country are met by its available *BC*. Recently, the *LCF* has become a very comprehensive indicator of environmental quality and an increasing number of environmental studies employ it for a correct assessment of environmental quality. The research objective is to evaluate the influences of *ER*, economic growth and green electricity on the *LCF* by considering some important institutional variables, such as corruption control and bureaucracy quality.

Institutional forces, such as the efficacy of corruption control measures and the quality of bureaucratic systems, wield significant influence over climate control initiatives. Corruption can be defined as the abuse of public power by officials for personal gain. Its detrimental effects encompass impeding economic progress and disrupting decision-making processes, thereby hampering societal development (Erum and Hussain, 2019). Corruption can exert a profound impact on the formulation and execution of pro-environmental policies, as influential business groups may impede the enactment of stringent ecological regulations by exerting influence on public officials. Corrupt governments are often engaged in activities such as bribery, misallocation of resources and inefficient management of the ecological footprint, all of which contribute to heightened environmental degradation (Salman *et al*., 2022).

According to Ren *et al*. (2021), corruption can promote harmful and weak ecological laws, delay and restrict the enforcement of ecological regulations, and divert resources from environmental saving projects to other activities. Corrupt institutions not only serve as constraints on domestic innovation but also impede the effective transfer of foreign technology, thereby stifling the progress of knowledge diffusion and economic development. Thus, Ozturk *et al*. (2019) argued that corruption decreases energy efficiency. In addition to this, bureaucracy quality is an important pillar of good governance. In most countries, the decision-making has been allocated to unelected individuals, which poses a certain risk to the citizens and the environment. According to Alola *et al*. (2022), red-tapism has adversely affected the EU's progress on climate control by reducing energy transition and enhancing complicated permission processes for renewable energy generation. According to Barsi *et al*. (2021), bureaucracies play an undeniable role in environmental protection since they employ millions of individuals around the globe, implement most ecological regulations and provide a link between different sectors of the economy and the government. Indeed, government change and other factors can affect environmental policies; however, strong institutional quality and higher quality of bureaucracy act as a shock absorber and minimize changes in policies. In countries with better bureaucracy quality, bureaucracy is usually independent of political pressure and follows a well-established procedure in decision-making (ICRG, 2023). Thus, consistent environmental policies and practices can be adopted to promote environmental quality in better democracies and vice versa (Alola *et al*., 2022).

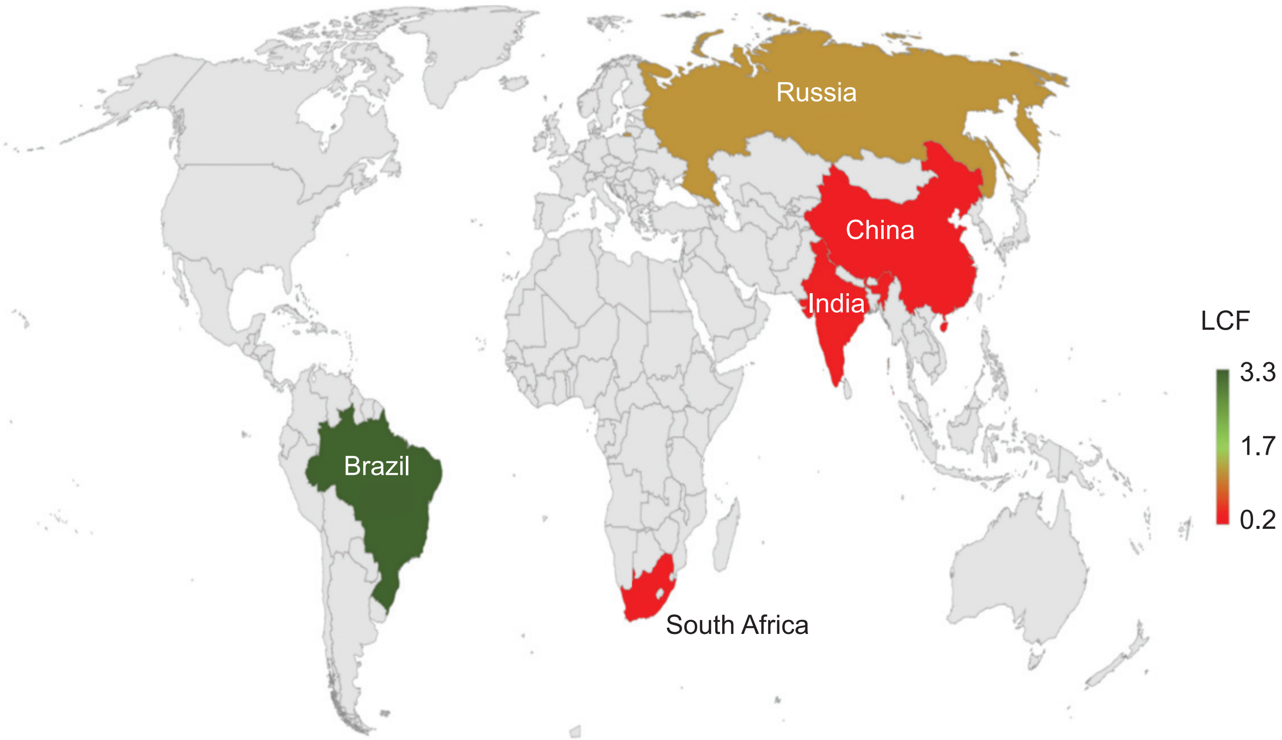
In this study, a sample of BRICS countries was chosen to explore this topic. Haseeb *et al*. (2019) and Haseeb *et al*. (2023) argued that BRICS countries are facing substantial environmental issues due to their increasing development. Over the past decade, BRICS countries have demonstrated a remarkable economic growth rate of 6.5%, making a substantial contribution of 23% to the global gross domestic product (GDP) (Tang *et al*., 2022). Among the BRICS countries, four countries (India, Brazil, China and Russia) stand among the top seven countries with the highest CO_2 emissions. Additionally, India and China are prominent among the world's leading energy-consuming countries (Khan *et al*., 2020).

Figure 1: Trends of green electricity (per capita) in BRICS



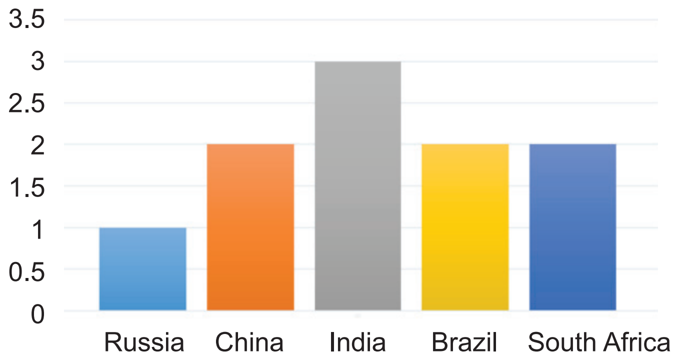
Source: OWD (2022)

Figure 2: Geographical distribution of *LCF* in BRICS (2018)



Source: GFN (2023)

Figure 3: Bureaucracy quality in BRICS (2018)



Source: ICRG (2020)

The BRICS countries have demonstrated a growing propensity to integrate *GE* into their energy portfolios as a strategic means to attain sustainable economic expansion. The *GE* has increased in BRICS over the studied period (Figure 1) but the situation regarding the use of *GE* is not very encouraging in India and South Africa. As shown in Figure 2, the *LCF* values in China, South Africa and India are 0.24, 0.26 and 0.37, respectively, indicating that these three countries have very low environmental quality, and their footprints are higher than *BC*.

Interestingly, Brazil and Russia are among the countries with the largest biocapacity, and their biocapacity reserves are important for the whole world as indicated by *LCF* values of more than 1 for these countries. Nevertheless, these countries are also facing a substantial reduction in their biocapacity, which makes the selection of the BRICS sample even more important. According to ICRG (2023), most BRICS countries struggle with corruption control and their scores on the corruption index on a scale of 6 are very low, *i.e.*, Russia (1.5), Brazil (2), China (2), India (2.5) and South Africa (2.5). Likewise, the performance of BRICS in terms of bureaucracy quality (Figure 3) on a scale of 4 is not impressive either, *i.e.*, Russia (1), Brazil (2), China (2), South Africa (2) and India (3). This indicates that BRICS struggle to maintain a reasonable level of bureaucracy quality and corruption control, and this situation can adversely affect their environmental targets.

This study systematically investigates the ramifications of environmental regulations and green electricity on the *LCF*, incorporating variables related to corruption control and bureaucracy quality into the analytical framework. Notably, there is a dearth of existing research with a comparable focus. Consequently, this research presents distinctive findings that significantly contribute to the enhancement of environmental quality, thereby filling a critical gap in the scholarly literature. Secondly, this study also assesses the linkage between economic growth and the *LCF* by following the notion of the load capacity curve (LCC) in the context of environmental regulations, green electricity, corruption control and bureaucracy quality. The study uses a reliable methodology (CS-ARDL) to report results robust to panel data issues, such as CSD, serial correlation, heterogeneity, mixed integration and endogeneity. The CCEMG method is used to check the robustness of long-run empirical outcomes. Furthermore, the causality method of Emirmahmutoglu and Kose (2011) is used because it accounts for CSD, fractional integration and heterogeneity.

2. Literature Review

In recent years, economists and environmentalists have focused on controlling environmental pollution and realizing sustainable development. In this context, it is a major challenge to use an appropriate proxy of environmental quality or environmental degradation in environmental studies. Popular measures, such as CO_2 emissions and the *EFP*, are overwhelmingly used in environmental economics literature to depict the degradation of the environment. However, various studies have also criticized these measures since CO_2 is restricted to measuring the effects of energy utilization and the *EFP* overlooks biocapacity, which is considered a significant factor on the supply side (Pata, 2021). Thus, Siche *et al*. (2010) provided the option to calculate an appropriate indicator of environmental quality by utilizing data on biocapacity and the *EFP* (*BC*/*EFP*).

Following this suggestion, studies started using the *LCF* as a comprehensive indicator of ecological quality. In this context, Dogan and Pata (2022) performed a comprehensive analysis of US data and found that economic development of the USA decreased the *LCF* at the initial stages; however, higher development stimulates the *LCF*, leading to a U-shaped curve between development and the *LCF*, which they called the load capacity curve (LCC). They supported this relationship by linking it with the popular "environmental Kuznets curve (EKC)" hypothesis and suggested that higher growth levels improve the *LCF*. They also included some other factors in their empirical model, such as renewable energy, research and development and ICT, and found that these variables boost the *LCF*. Following the same notion, the study of Pata and Kartal (2022) conducted a comparison of the *LCF* with other indicators, such as the *EFP* and CO_2, and revealed that both EKC and LCC exist in South Korea.

After this, the literature on the *LCF* increased; however, not many studies have focused on the concept of LCC. Nevertheless, studies have illustrated certain drivers of the *LCF* and reported increasing or decreasing influences of certain factors on the *LCF*. For instance, Pata and Isik (2021) revealed that income and energy intensity decrease the *LCF* and human capital promotes the *LCF* in China. The work of Akadiri *et al*. (2022) concluded that financial globalization and green energy improve the *LCF* while income mitigates the *LCF* in India. Khan *et al*. (2022) illustrated that income and population decrease the *LCF* while green energy augments the *LCF* in G7 and E7. Adebayo *et al*. (2022) also conducted a comparison between *EFP*, *LCF* and CO_2 drivers in Thailand, and established that natural resources, import, income and export improve ecological quality. However, the pollution haven effect depends on the selection of environmental measures. Awosusi *et al*. (2022) illustrated that globalization and innovation increase the *LCF* in South Africa while energy consumption lessens it. Xu *et al*. (2022) revealed that conventional energy use and renewable energy mitigate the *LCF* in Brazil. On the other hand, Liu *et al*. (2022) revealed that green energy and innovation increase the *LCF* in South Africa but income and fossil energy lower it.

The literature on the *LCF* is growing and studies have inspected the impacts of green sources of energy, economic growth and some other variables on the *LCF*. However, many important variables that might influence the *LCF* have not been considered by previous studies. Among these, environmental regulations can influence environmental quality. According to Danish *et al*. (2020), *ER* can have a beneficial impact on increasing energy efficiency and decreasing pollutant energy use. According to Murshed *et al*. (2021), *ER* can stimulate renewable energy production and lessen the adverse effects of development on the environment. However, if environmental regulations are not stringent, the pollution haven effect can increase environmental pollution (Ahmed *et al*., 2021). Following these theoretical arguments, empirical works have inspected the influence of *ER* on emissions and the *EFP*. For instance, Wenbo and Yan (2018) established that *ER* decrease emissions, exhibiting some regional variations in China. Danish *et al*. (2020) proved that *ER* decrease CO_2 in BRICS. However, Zhang *et al*. (2019) noted that *ER* along with industrial pollution boost pollution levels as well as reduce pollution levels in various areas by developing a synergistic effect. Nevertheless, *ER* improve the environmental quality at the national level. Wang and Wei (2020) provided the view that *ER* hinder economic progress in some emerging countries; thus, *ER* should be carefully designed to avoid their possible negative effects on growth.

Omojolaibi and Nathaniel (2022) illustrated that *ER* in the MENA region do not influence the *EFP*; however, growth and energy increase the *EFP*. Murshed *et al*. (2021) suggested that *ER* limit the *EFP* and also reinforce the environmental benefits of green energy. Likewise, Ahmed *et al*. (2022) illustrated that *ER* and democracy curb the *EFP* in G7. Thus, *ER* can be promoted to decrease the *EFP*.

Similar to environmental regulations, the impacts of corruption control on the *LCF* have been overlooked in previous studies. However, some works have explored the impacts of *CRC* on ecological degradation. According to Wang *et al*. (2018), controlling corruption decreases CO_2 in BRICS through economic growth. However, Ren *et al*. (2021) found that corruption boosts emissions in the short run while in the long run, it decreases emissions in China's provinces. According to Salman *et al*. (2022), corruption limits domestic innovation and technology transfer in the developing world, which increases the *EFP*. According to Erum and Hussain (2019), corruption increases the mismanagement of natural resources and also hinders economic growth. In earlier work, Pellegrini and Gerlagh (2006) suggested that corruption is an important driving factor of environmental policy. The study by Ozturk *et al*. (2019) depicted that reducing corruption boosts energy efficiency in a panel of sixty countries. Thus, corruption control is necessary to reduce energy use. Conversely, Zaidi *et al*. (2021) found that corruption decreases emissions in OECD countries. Besides, the bureaucracy quality and environmental quality nexus has been overlooked in previous studies. However, the work of Alola *et al*. (2022) is an exception as they revealed the nexus between bureaucracy quality and CO_2 in EU countries and found that *BQ* decreases CO_2 and improves the quality of the environment.

In the extant literature, the *LCF* has been comprehensively scrutinized in relation to economic growth, green energy sources, globalization, export, import and energy consumption, among other variables. Nonetheless, a conspicuous gap in the existing scholarly discourse pertains to the absence of empirical investigations exploring the interconnections between environmental regulations, corruption control, bureaucracy quality and their collective influence on the *LCF*. Hence, employing the framework of the load capacity curve, this research systematically evaluates the impacts of corruption control, environmental regulations, bureaucracy quality and green electricity on the *LCF*, thereby enhancing our understanding of the dynamics governing the *LCF*.

3. Data and Methodology

The study's framework revolves around the LCC concept, positing that initial stages of growth diminish the *LCF*, whereas reaching a specific threshold of growth enhances the *LCF*. Consequently, a discernible U-shaped relationship is observed between the *LCF* and GDP (Dogan and Pata, 2022). It is noteworthy that this LCC concept is in line with the concept of the EKC (Pata and Kartal, 2022). Environmental regulations are strongly linked with the reduction in environmental degradation, and they also help realize the environmental benefits of growth by reducing the detrimental impacts of income on environmental quality (Ahmed *et al*., 2022). Green electricity is beneficial to ecological quality, and it also helps decrease electricity generation from traditional fossil fuels (Li *et al*., 2021). The use of alternative energy accelerates progress towards sustainable growth and reduces ecological concerns. Corruption is an important determinant of environmental policy (Pellegrini and Gerlagh, 2006). Corruption control can decrease energy use (Ozturk *et al*., 2019) and improve environmental quality (Zaidi *et al*., 2021). Bureaucracy quality may help improve the consistency of environmental policy. According to Alola *et al*. (2022), bureaucracy quality is an important driver of environmental quality. Thus, we construct the following model:

$$(LCF)_{it} = \beta_0 + a_1 EG_{it} + b_2 (EG)^2_{it} + c_3 ER_{it} + d_4 GE_{it} + \mu_{it} \tag{1}$$

where EG and EG^2 are used to assess the LCC hypothesis and they denote GDP per person (USD 2015) and the quadratic term of the GDP, respectively. ER denotes environmental regulations, GE is green electricity per person and μ is the error term. Furthermore, Model 2 is constructed by adding bureaucracy quality (BQ) and corruption control (CRC).

$$(LCF)_{it} = \beta_0 + a_1 EG_{it} + b_2 (EG)^2_{it} + c_3 ER_{it} + d_4 GE_{it} + e_5 BQ_{it} + f_6 CRC_{it} + \mu_{it} \tag{2}$$

Panel data for BRICS (Brazil, Russia, India, China and South Africa) for the period from 1992 to 2018 are analysed; the selected span depends upon data availability. The selected data series was transformed into natural logarithms except *ER*, which are entered as a percentage. Evidently, the datasets of *CRC* and *BQ* had many values of one; thus, a constant was added for their log transformation. The data for the dependent variable *LCF* (*BC*/*EFP*) were collected from GFN (2022). Green electricity measured by renewable electricity (per person kWh) came from OWD (2022). Two proxies are commonly used for environmental regulations, namely environmental taxes and environmental patents. Data relating to environmental taxes are not available for the selected period; thus, this study uses the proxy of environmental patents as a percent of aggregate patents to represent *ER* following the recent studies of Ahmed *et al*. (2022) and Danish *et al*. (2020). The datasets of *ER* came from the OECD (2021). Corruption control is measured using the corruption index, which ranges from 0 to 6. Higher values of *CRC* indicate less corruption and vice versa. Bureaucracy quality is represented by the index of bureaucracy quality, which ranges from 0 to 4. A higher rating on this scale indicates superior bureaucratic quality, whereas a lower rating corresponds to diminished quality in bureaucratic operations. The datasets for *CRC* and *BQ* came from ICRG (2020).

3.1 Methodology

The study intends to evaluate the long-run impacts of *CRC*, *BQ* and *ER* on the *LCF* in BRICS. Before analysing the panel data for BRICS, it is important to perform some preliminary tests to know about the characteristics of the data. To do so, this study initially applies the Breusch–Pagan LM test to trace any possible dependence among the series. This investigation is further improved by applying the Pesaran CD test, which is a popular test to analyse CSD in panel datasets. This test is specified below:

$$PCDT = \sqrt{\frac{2e}{m(m-1)}}\left(\sum_{i=1}^{m-1}\sum_{j=i+1}^{m}\widehat{A}_{ij}\right) \tag{3}$$

where *PCDT*, $\widehat{A}_{ij}$, *e* and *m* refer to the Pesaran CD test, pair-wise correlation, time and sample size, respectively.

In the next part of the investigation, slope homogeneity is examined by the use of Pesaran and Yamagata (2008) tests. This methodology applies $\tilde{\Delta}$ and adjusted $\tilde{\Delta}$ tests for revealing heterogeneity in the model. It is essential to perform these tests since the presence of homogeneity requires certain first-generation tests for investigating the unit roots, cointegration and long-run coefficients. However, if homogeneity is absent, second-generation methodologies are suitable.

Given the absence of homogeneity and cross-sectional independence, the cross-sectional IPS (CIPS) method is preferred, which can recognize unit roots in series in heterogeneous panels exhibiting CSD. Alongside this, the cross-sectional ADF (CADF) method is also utilized to improve the analysis. The benefits offered by both these Pesaran's (2007) techniques are similar. The equation for CADF is articulated below:

$$\Delta K_{it} = \beta_i + a_i K_{it-1} + b_i \overline{z}_{t-1} + \sum_{j=0}^{p} c_{ij} \Delta \overline{K}_{it-1} + \sum_{j=0}^{p} d_{ij} \Delta K_{it-1} + \varepsilon_{it} \tag{4}$$

where β denotes the intercept, ε depicts the residual term, K_{it} stands for the analysed variable and P denotes lag order. Furthermore, $\overline{z}_{t-1}$ and $\Delta\overline{K}_{it-1}$ depict the average of cross-sections. In this test, the null hypothesis can only be rejected if one of the individuals could become stationary. The model for CIPS is as follows:

$$CRIPS = \frac{1}{n}\sum_{i=1}^{n} CRADF_i \tag{5}$$

where *CRIPS* denotes the Pesaran CIPS method. *CRADF* depicts the average of every CADF, which comes from Equation 4.

Next, the main analysis to reveal the long-run equilibrium connection is performed. In this regard, Westerlund's (2008) method is applied. This method uses group and panel tests (DHg and DHp) to check the cointegration. By employing the Durbin–Hausman principle, this technique uses common factors and accounts for independence and heterogeneity in data. The outcomes of this test are robust to stationary regressors and endogeneity problems.

Given the cointegration in models, the CS-ARDL method is used. The CS-ARDL of Chudik *et al*. (2016) is a very useful test for datasets exhibiting heterogeneity and dependence. In addition, this method also off ers reliable features for countering endogeneity, non-stationarity and serial correlation. This test can be written as follows:

$$\Delta LCF_{i,t} = \vartheta_i + \sum_{j=1}^{p} \varphi_{it} \Delta LCF_{i,t-j} + \sum_{j=0}^{p} \varphi'_{ij} AVE_{i,t-j} + \sum_{j=0}^{p} \varphi'_{it} \overline{sc}_{t-j} + \varepsilon_{i,t} \tag{6}$$

where *LCF* depicts the dependent variable, *AVE* stands for regressors and $\overline{sc}_t = (\Delta\overline{LCF}_{t,} \overline{AVE}_t{}')'$ illustrates the average of the cross-section.

Robustness of results requires using another method with similar benefits. Thus, the common correlated effects mean group (CCEMG) technique is adopted because it is useful in panels exhibiting dependence and heterogeneity (Chudik and Pesaran, 2015). This test is used to check the robustness of long-run coefficients.

Next, the causal dynamics are examined using the causality test by Emirmahmutoglu and Kose (2011). This test adheres to the Toda and Yamamoto causality methodology, demonstrating its flexibility by not necessitating the assessment of the order of integration. In addition, it allows stationary variables, as well as variables with I(1) integration level; thus, variables with different orders of integration can also be included under the Emirmahmutoglu-Kose framework. Emirmahmutoglu and Kose (2011) proposed a method to modify the modified VAR technique of Toda and Yamamoto by using a VAR model at I(0) with additional d_{max} to disclose the causality between variables in heterogeneous panels. This test offers reliability for panel data with dependence and heterogeneity, and the presence or absence of cointegration does not affect its outcomes.

4. Results and Discussion

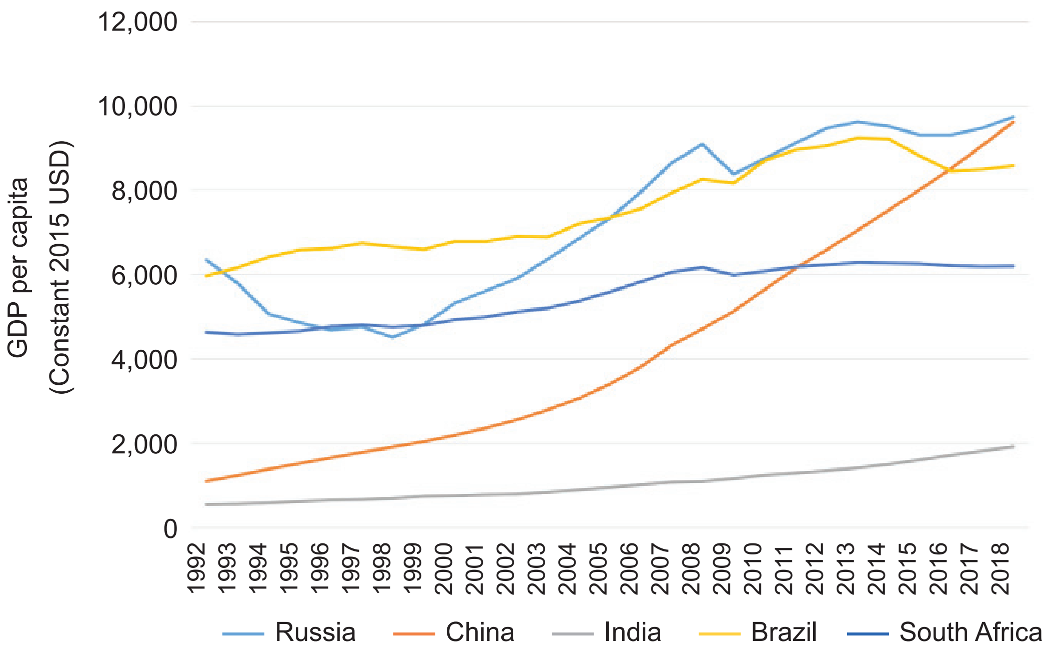
The descriptive statistics of the variables from 1992 to 2018 for the BRICS panel are given in Table 1. The minimum value of the *LCF* is over 1 and the high biocapacity of Brazil and Russia contribute to achieving this average. Green electricity increased during the selected period, and the mean value was 744.1027 for the panel. *EG* has a very high standard deviation mainly due to the rapid progress in BRICS over the period of analysis. The minimum value (545.3995) is very low compared to the maximum value (9 739.900) since there was considerable growth and heterogeneity in data from 1992 to 2018. The trends of *EG* are provided in Figure 4 for all the sample countries. The statistics of *ER* indicate that environmental patents had a mean value of only 9, which means that on average, green patents were just 9% of overall patents during the period under study. The averages of *BQ* and *CRC* were just above 2, which indicates considerable institutional issues as the total values of these indices can be 4 and 6, respectively.

Table 1: Descriptive statistics

	LCF	*LEG*	*ER*	*GE*	*BQ*	*CRC*
Mean	1.2038	5141.429	9.0299	744.1027	2.1482	2.4926
Median	0.4910	5647.059	9.1100	303.8595	2.0000	2.5000
Maximum	4.3667	9739.900	16.8000	2364.499	4.0000	5.0000
Minimum	0.2177	545.3995	2.4100	3.6837	1.0000	1.0000
Std. dev.	1.2489	2856.273	2.8449	742.0495	0.7073	0.8936

Note: Data before natural log conversion were used to calculate descriptive statistics.
Source: Authors' own calculations

Figure 4: Trends of economic growth



Source: World Bank (2023)

Next, the VIF figures are computed in Table 2. The VIF values for *BQ*, *EG*, *CRC*, *GE* and *ER* are 2.55, 2.21, 1.69, 1.66 and 1.32, respectively, suggesting that there is no multicollinearity in the BRICS panel as all these values are less than 5.

After this, tests are applied in Table 3 to assess the CSD in the panel. The verdicts of the LM technique indicate that *EG*, *ER*, *GE*, *BQ* and *CRC* demonstrate dependence; thus, there is CSD in the BRICS data. Similarly, the CD test confi rms this conclusion for *EG*, *ER*, *GE*, *BQ* and *CRC*.

Table 2: VIF output

Variables	VIF	1/VIF
BQ	2.55	0.392
EG	2.21	0.453
CRC	1.69	0.592
GE	1.66	0.604
ER	1.32	0.7557
Mean VIF	1.89	

Source: Authors' own calculations

Table 3: Cross-sectional dependence (CSD) tests

	Breusch–Pagan LM	Pesaran CD
LCF	127.444* [0.000]	9.018* [0.000]
EG	240.976* [0.000]	15.515* [0.000]
ER	21.461** [0.018]	2.855* [0.004]
GE	140.410* [0.000]	11.519* [0.000]
BQ	82.548* [0.000]	6.375* [0.000]
CRC	62.121* [0.000]	6.738* [0.000]

Note: ** and * refer to 5% and 1% significance.
Source: Authors' own calculations

Proceeding forward, the Pesaran-Yamagata test in Table 4 unveiled that the statistics of $\tilde{\Delta}$ and adjusted $\tilde{\Delta}$ are 8.390 and 9.295 in Models 1 and 2, respectively, and their corresponding *p*-values are zero. Hence, these significant statistics reject the assumption of homogeneity. Similar findings are noticed for Model 2; thus, the dataset demonstrates heterogeneity.

Table 4: Test to check slope homogeneity

Test	Model 1	Model 2
$\tilde{\Delta}$	8.390* [0.000]	7.500* [0.000]
$\tilde{\Delta}$ *adjusted*	9.295* [0.000]	8.715* [0.000]

Note: * specifies 1% significance; Model 1: (*LCF* = *EG*, *EG*^{2}, *ER*, *GE*); Model 2: (*LCF* = *EG*, *EG*^{2}, *ER*, *GE*, *BQ*, CC)
Source: Authors' own calculations

Dealing with CSD and heterogeneity in panel data requires selecting second-generation tests for unit root examination. Consequently, the CIPS test is applied in Table 5 along with the CADF test. The CIPS statistics reveal that *CRC*, *BQ*, *EG* and *ER* are stationary while the other variables are also stationary at 1(1). However, the CADF statistics revealed that variables do not have unit roots at 1(1), while only *CRC* is stationary at 1(0). Although there are certain differences in the results of both tests, the stationarity of variables at 1(1) is strongly confirmed. Nevertheless, there are also some indications of mixed order of integration, which must be taken care of in the subsequent analysis.

As indicated in the previous investigation, the BRICS dataset exhibits mixed integration, CSD and heterogeneity issues, simultaneously; hence, the cointegration analysis must address all these issues. Thus, Westerlund's (2008) method is chosen, and the verdicts in Table 6 illustrate the *p*-values of 0.020 and 0.070 for DHg and DHp statistics in Model 1, respectively, which are significant. Likewise, the *p*-values of 0.024 and 0.094 confirm the significance of DHg and DHp statistics in Model 2, respectively. This suggests the rejection of the null hypothesis and a confirmation of cointegration in the data.

Table 5: Tests for unit root inspection

	CADF		CIPS	
	Level	Δ	Level	Δ
LCF	−2.800	−3.143*	−2.190	−3.857
EG	−2.463	−3.085**	−2.802***	−3.524*
ER	−2.688	−5.030*	−4.684*	−6.110*
GE	−2.261	−3.840*	−2.010	−5.241*
BQ	−1.637	−4.430*	−4.456*	−4.796*
CRC	−3.650*	−4.743*	−3.609*	−5.641*

Note: CVs: 1% (−3.10), 5% (−2.86), 10% (−2.73); ***, ** and * show 10%, 5% and 1% significance levels.
Source: Authors' own calculations

Table 6: Westerlund (2008) test

Model 1 (*LCF = EG, EG2, ER, GE*) Model 2 (*LCF = EG, EG2, ER, GE, BQ, CRC*)		
	Model 1	**Model 2**
DHg	–2.045** [0.020]	–1.972 ** [0.024]
DHp	–1.459*** [0.072]	–1.319*** [0.094]

Note: *** and ** show 10% and 5% significance levels.
Source: Authors' own calculations

After the cointegration analysis, the long-run analysis is initiated. In this context, first, Model 1 is estimated without corruption control and bureaucracy quality. The results of Model 1 obtained by using the CS-ARDL in Table 7 reveal that *EG* lessens the *LCF* with an elasticity of 0.376, implying that currently, a 1% enhancement in *EG* leads to a decrease of 0.376% in the *LCF*. This indicates that the BRICS growth level places enormous stress on the consumption of natural resources and biocapacity reserves. In recent decades, BRICS economic progress has substantially increased; consequently, this country group has used 40% of global energy. The rapid development in BRICS has increased the use of resources, generating 41% of global CO_2 emissions (Qin and Ozturk, 2021; Peng *et al*., 2022). Thus, a reduction in the ecological quality on account of an improvement in *EG* is sensible, and it matches the verdicts of Akadiri *et al*. (2022) and Khan *et al*. (2022) in the context of India and G7, respectively.

However, this study also uses the quadratic form of *EG*, and the resultant coefficient exhibits significance. More precisely, boosting EG^2 by 1% raises the *LCF* by 0.026%, showing that if BRICS could continue their development, the quality of the environment would improve after reaching a threshold level of *EG*, resulting in a U-shaped association between the *LCF* and *EG*. This proves the notion of LCC and corresponds to the outcomes of Pata and Kartal (2022), who revealed the LCC in South Korea. This evidence also matches the conclusions of Dogan and Pata (2022) in the case of the USA. Although studies on LCC in the context of BRICS are not available, the study of Dong *et al*. (2017) suggests the EKC by using CO_2 emissions in BRICS, which supports the idea that higher growth can be beneficial for environmental quality in BRICS. This is because improvements in innovation, technology, environmental consciousness and environmental regulations, which tend to improve ecological quality, are more likely to be observed at higher levels of growth. In addition, a similar finding holds in the short run. Thus, this study verifies the LCC hypothesis in both the short and long run for BRICS.

Table 7: Short-run and long-run results (CS-ARDL)

Variable	Model 1		Model 2	
Short-run	**Coefficients**	***Z*-values**	**Coefficients**	***Z*-values**
EG	−0.586**	−2.43	−0.559**	−2.26
EG²	0.046*	5.67	0.041*	5.125
ER	0.005***	1.86	0.006**	2.04
GE	0.118*	2.91	0.127**	2.12
BQ	–	–	0.008**	2.20
CRC	–	–	0.018**	2.39
***ECM* (−1)**	−0.867*	−4.11	−0.836*	−3.54
Long-run				
EG	−0.376**	−2.32	−0.379**	−2.00
EG²	0.026*	4.29	0.028*	4.07
ER	0.003**	2.50	0.003**	2.31
GE	0.073**	2.35	0.076**	2.24
BQ	–	–	0.005**	2.48
CRC	–	–	0.007*	3.52

Note: ***, ** and * show 10%, 5% and 1% significance.
Source: Authors' own calculations

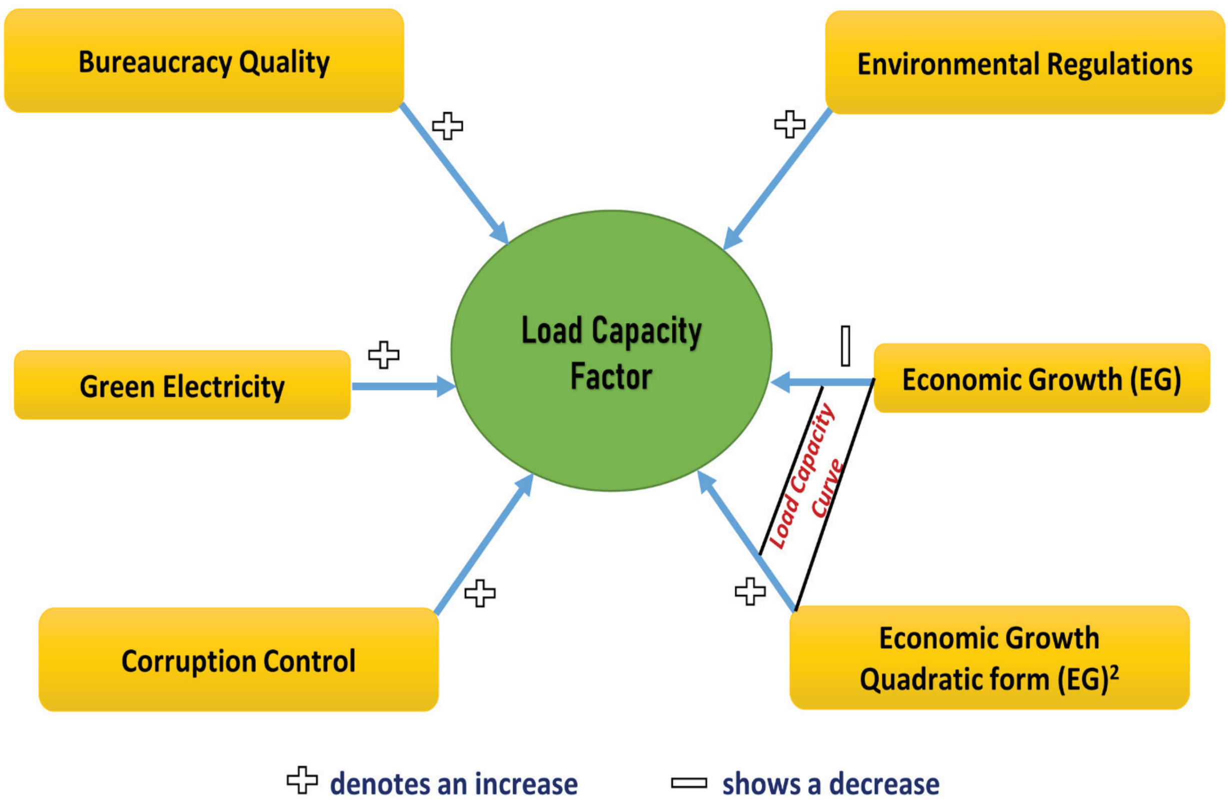
Regarding *ER*, the coefficient of 0.003 supports the view that *ER* can boost the *LCF* and thereby, improve environmental quality. However, increasing *ER* by 1% only corresponds to a 0.003% reduction in the *LCF*. There are no studies on the *ER* and *LCF* nexus; however, previous studies have evidenced that increasing *ER* can be helpful in decreasing environmental degradation. For example, Danish *et al.* (2020) revealed that *ER* are beneficial to reducing emissions in the context of BRICS. Likewise, Wenbo and Yan (2018) found that boosting *ER* limits emissions in China. According to Ahmed *et al.* (2022), stringent ecological regulations reduce the *EFP* in the G7. Thus, this finding corroborates previous findings and adds to the literature by proving that even when we use a comprehensive measure of environmental quality (*LCF*), environmental regulations boost environmental quality. This positive connection between *ER* and the *LCF* is logical because *ER* can boost energy saving, reduce consumption of fossil fuels and promote green energy consumption (Murshed *et al*., 2021), which can in turn intensify the *LCF*.

Next, boosting *GE* by 1% boosts the *LCF* by 0.073%, implying that green electricity encourages the *LCF* in BRICS. Once again, findings on the *GE* and *LCF* nexus are not available to support this verdict. However, there are empirical findings that support this effect: for instance, Murshed *et al*. (2022) indicated that renewable electricity decreases the *EFP* in Bangladesh, Qin *et al*. (2021) proved that *GE* decreases emissions in emerging countries, Bélaïd and Youssef (2017) indicated that *GE* mitigates emissions, and Dai *et al*. (2023) revealed that *GE* curbs the *EFP*. Enhancing the use of green electricity can decrease the production of electricity from conventional energy, which can in turn improve ecological quality and help achieve an energy transition. The positive effects of *GE* on environmental quality are not surprising since green energy sources are beneficial for environmental quality. Also, per capita *GE* has increased in almost all the BRICS countries: for instance, *GE* increased from 108.504 to 1084.791 kWh from 1992 to 2018 in China, from 1479.796 to 2364.499 in Brazil, and from 1164.488 to 1317.493 kWh in Russia. Also, *GE* adds to the environmental quality and shows similar behaviour in the short run. Summing up, an increase in *GE* promotes environmental quality in BRICS. The ECM coefficient denotes a high convergence rate of almost 87% per year.

After this, corruption control and bureaucracy quality were added to the model, and Model 2 was estimated using the CS-ARDL. The findings of *EG*, *ER* and *GE* are found to be consistent. In addition, corruption control boosts the *LCF*, *i.e.*, a 1% increase in *CRC* raises the *LCF* by 0.007%, denoting that controlling corruption can have a favourable influence on environmental quality. Once again, studies on the *LCF* and corruption control are unavailable and this finding is novel in the case of BRICS. Nevertheless, this result is consistent with the findings of past studies that have indicated a reduction in CO_2 due to an increase in corruption control in Chinese provinces (Ren *et al*., 2021) and the OECD (Zaidi *et al*., 2021). Also, boosting corruption control can encourage energy efficiency (Ozturk *et al*., 2019), which can play a supportive role in boosting environmental quality. As discussed before, corruption is generally linked with misuse of resources, ineffective footprint management practices (Salman *et al*., 2022), delays in environmental policies, ineffective implementation of ecological laws (Ren *et al*., 2021) and other issues that can hinder improvement in environmental quality. Hence, improvement in corruption control can help avoid such problems leading to an increase in the *LCF*. Also, in the short run, corruption control exhibited similar behaviour. Lastly, bureaucracy quality increases the *LCF*, *i.e.*, an increase of 1% in *BQ* leads to an increase of 0.005% in the *LCF*. Boosting bureaucracy quality can help avoid issues such as red-tapism, delays in decision-making and inconsistency in environmental policies, which can help improve environmental quality. This outcome matches the finding of Alola *et al*. (2022), who argued that increasing bureaucracy quality decreases red-tapism and unnecessary delays in environmental decisions, which decrease CO_2 emissions in the EU. Also, in the short run, bureaucracy quality boosts the *LCF*. Besides, Model 2 also shows a convergence rate of almost 84% per year. The long-run estimates of the study are shown in Figure 5.

Next, the estimates of CCEMG in Table 8 depict that *ER* and *GE* improve the *LCF* in BRICS. Also, improving bureaucracy quality and corruption control increases the *LCF*. In addition, the *LCF* is indicated by a positive coefficient of EG^2 and a negative coefficient of *EG*. Thus, the consistency of results is evident from the results provided in Table 8.

Figure 5: Long-run results



Source: Authors' own design

Table 8: Robustness check (CCEMG)

Variable	Model 1	Model 2
EG	−0.924** [−2.14]	−0.824** [−2.48]
EG^2	0.042* [3.82]	0.051* [3.24]
ER	0.003** [2.35]	0.002*** [1.88]
GE	0.107*** [1.90]	0.119** [2.27]
BQ	–	0.026** [2.30]
CRC	–	0.031* [3.05]
Constant	−3.718* [−5.34]	−3.883* [−4.26]

Note: ***, ** and * show 10%, 5% and 1% significance.

Source: Authors' own calculations

Subsequently, the Emirmahmutoglu-Kose test is employed to systematically investigate the causal relationships between the variables in an empirical context. In this particular context, the findings presented in Table 9 signify the presence of a feedback association between *EG* and the *LCF*, highlighting the interdependent relationship between these variables. There is one-way causality from *ER* to the *LCF*, which shows that changes in *ER* will infl uence the *LCF*. Similarly, both corruption control and bureaucracy quality Granger-cause the *LCF*. Nevertheless, the bidirectional causality observed between *GE* and the *LCF* suggests a mutual relationship, indicating that alterations in green electricity levels can aff ect the *LCF*. Additionally, BRICS countries modify their electricity production practices in an eff ort to enhance environmental quality, a response to the increasing *EFP* and diminishing biocapacity. This results in a feedback eff ect between these two variables.

Table 9: Emirmahmutoglu-Kose causality test

	Panel Fisher	Prob.
LEG* to *LCF	17.639***	0.061
LCF* to *LEG	16.839***	0.078
ER* to *LCF	23.813*	0.008
LCF* to *ER	13.013	0.223
GE* to *LCF	16.739***	0.080
LCF* to *GE	17.146***	0.071
BQ* to *LCF	59.873*	0.000
LCF* to *BQ	6.412	0.780
CRC* to *LCF	16.932***	0.076
LCF* to *CRC	2.192	0.995

Note: *** and * describe 10% and 1% significance.
Source: Authors' own calculations

5. Conclusion and Policy Direction

This study examined the nexus between green electricity, environmental regulations, economic growth and the *LCF* by evaluating the roles of corruption control and bureaucracy quality. To explore this relationship, the study scrutinized the data for BRICS from 1992 to 2018 and established the following conclusions:

Green electricity boosts the *LCF*, and environmental regulations are also beneficial in increasing the *LCF* in BRICS. Green electricity also enhances the *LCF*. The connection between *EG* and the *LCF* is a U-shaped curve, supporting the concept of the load capacity curve. Thus, *EG*, which currently reduces the *LCF*, can boost the *LCF* levels after reaching a threshold level. Likewise, corruption control and bureaucracy quality increase and Granger-cause the *LCF*.

The findings of this paper provide some important insights for environmental policymaking. BRICS need to strengthen their environmental regulations to enhance green energy utilization and discourage the use of conventional energy. In this regard, the strategy could be to offer tax reliefs on green technologies and green energy solutions. At the same time, an increase in carbon taxes can reduce the usage of fossil fuels. Likewise, electricity generation from green sources can be facilitated in these countries. Although green electricity (per capita) has increased in BRICS, the level of green electricity per capita is still low in India and South Africa. Thus, these countries should focus even more on the promotion of green electricity to boost their ecological quality.

At the same time, BRICS should strive to improve their corruption control mechanisms by improving the accountability of public institutions. Measures are necessary to reduce political influence and promote honesty and professionalism within the institutions. Separate institutes can be established for accountability and to maintain the checks and balances in public institutes, and such institutions must also be free from political pressure. Also, improvements are required in the bureaucracy and unnecessary hurdles in the adoption and production of green energy should be removed. It is also necessary to use modern technology and online information systems and procedures in institutional work. Modern online information systems can increase the transparency of procedures and help control corruption and unnecessary bureaucratic delays. In addition, steps are necessary to keep environmental policies separate from politics to ensure the stability of environmental policy.

The above policies will enhance the efficacy of environmental regulation and increase the use of green electricity in these countries. These policies will also facilitate reducing the harmful effects of development in BRICS on environmental quality. Enhancing green energy will also help these countries continue their development to achieve the possible environmental benefits at higher levels of growth. Hence, these policies will ensure effective climate control and thereby help BRICS achieve SDG 13.

This research, while possessing numerous merits, exhibits a specific focus on countries within the BRICS grouping. Consequently, the findings of this study hold relevance solely for developing countries. Moreover, the study concentrates exclusively on environmental sustainability, employing *LCF* indicators that do not encompass vital dimensions such as health and education. Consequently, the study's scope is restricted in its ability to inform comprehensive sustainable development policies, as critical facets essential for sustainable development are disregarded. Subsequent research endeavours have the potential to surmount these constraints by broadening the study sample size. Additionally, scholars are encouraged to explore comprehensive indicators of sustainable development, encompassing the previously overlooked dimensions of health and education. Furthermore, future investigations might delve into understanding the intricate dynamics between corruption control, bureaucracy quality and their impacts on sustainable growth, thereby enhancing the depth and breadth of scholarly contributions in this domain.

Acknowledgement

Funding: There was no funding, either externally or internally, towards this study.
Conflicts of interest: The authors hereby declare that this article was not submitted nor published elsewhere.

References

Adebayo, T. S., Pata, U. K., Akadiri, S. S. (2022). A comparison of CO2 emissions, load capacity factor, and ecological footprint for Thailand's environmental sustainability. *Environment, Development and Sustainability*, https://doi.org/10.1007/s10668-022-02810-9

Ahmed, Z., Ahmad, M., Rjoub, H., et al. (2022). Economic growth, renewable energy consumption, and ecological footprint: Exploring the role of environmental regulations and democracy in sustainable development. *Sustainable Development*, 30(4), 595–605, https://doi.org/10.1002/sd.2251

Ahmed, Z., Cary, M., Le, H. P. (2021). Accounting asymmetries in the long-run nexus between globalization and environmental sustainability in the United States: An aggregated and disaggregated investigation. *Environmental Impact Assessment Review*, 86, 106511, https://doi.org/10.1016/j.eiar.2020.106511

Akadiri, S. S., Adebayo, T. S., Riti, J. S., et al. (2022). The effect of financial globalization and natural resource rent on load capacity factor in India: an analysis using the dual adjustment approach. *Environmental Science and Pollution Research*, 29, 89045–89062, https://doi.org/10.1007/s11356-022-22012-0

Al-Mulali, U., Weng-Wai, C., Sheau-Ting, L., et al. (2015). Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation. *Ecological Indicators*, 48, 315–323, https://doi.org/10.1016/j.ecolind.2014.08.029

Alola, A. A., Okere, K. I., Muoneke, O. B., et al. (2022). Do bureaucratic policy and socioeconomic factors moderate energy utilization effect of net zero target in the EU? *Journal of Environmental Management*, 317, 115386, https://doi.org/10.1016/j.jenvman.2022.115386

Awosusi, A. A., Kutlay, K., Altuntaş, M., et al. (2022). A Roadmap toward Achieving Sustainable Environment: Evaluating the Impact of Technological Innovation and Globalization on Load Capacity Factor. *International Journal of Environmental Research and Public Health*, 19(6), 1–16, https://doi.org/10.3390/ijerph19063288

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., et al. (2018). How economic growth, renewable electricity and natural resources contribute to CO2 emissions? *Energy Policy*, 113, 356–367, https://doi.org/10.1016/j.enpol.2017.10.050

Barsi, R. L., Van Acker, E., Gailius, P., et al. (2021). Bureaucrats must take a bigger role in fighting climate change. *World Bank Blogs* [online]. Available at: https://blogs.worldbank.org/governance/bureaucrats-must-take-bigger-role-fighting-climate-change

Bélaïd, F., Youssef, M. (2017). Environmental degradation, renewable and non-renewable electricity consumption, and economic growth: Assessing the evidence from Algeria. *Energy Policy*, 102, 277–287, https://doi.org/10.1016/j.enpol.2016.12.012

Can, M., Ahmed, Z. (2022). Towards sustainable development in the European Union countries: Does economic complexity affect renewable and non-renewable energy consumption? *Sustainable Development*, 31(1), 439–451, https://doi.org/10.1002/sd.2402

Charfeddine, L. (2017). The impact of energy consumption and economic development on Ecological Footprint and CO2 emissions: Evidence from a Markov Switching Equilibrium Correction Model. *Energy Economics*, 65, 355–374, https://doi.org/10.1016/j.eneco.2017.05.009

Chudik, A., Mohaddes, K., Pesaran, M. H., et al. (2016). *Long-run effects in large heterogeneous panel data models with cross-sectionally correlated errors*. Leeds: Emerald Group Publishing Limited. ISBN 978-1-78560-787-5.

Chudik, A., Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393–420, https://doi.org/10.1016/j.jeconom.2015.03.007

Dai, J., Ahmed, Z., Sinha, A., et al. (2023). Sustainable green electricity, technological innovation, and ecological footprint: Does democratic accountability moderate the nexus? *Utilities Policy*, 82, 101541, https://doi.org/10.1016/j.jup.2023.101541

Danish, Ulucak, R., Khan, S. U.-D., et al. (2020). Mitigation pathways toward sustainable development: Is there any trade-off between environmental regulation and carbon emissions reduction? *Sustainable Development*, 28(4), 813–822, https://doi.org/10.1002/SD.2032

Dogan, A., Pata, U. K. (2022). The role of ICT, R&D spending and renewable energy consumption on environmental quality: Testing the LCC hypothesis for G7 countries. *Journal of Cleaner Production*, 380(1), 135038, https://doi.org/10.1016/j.jclepro.2022.135038

Dong, K., Sun, R., Hochman, G. (2017). Do natural gas and renewable energy consumption lead to less CO2 emission? Empirical evidence from a panel of BRICS countries. *Energy*, 141, 1466–1478, https://doi.org/10.1016/j.energy.2017.11.092

Emirmahmutoglu, F., Kose, N. (2011). Testing for Granger causality in heterogeneous mixed panels. *Economic Modelling*, 28(3), 870–876, https://doi.org/10.1016/j.econmod.2010.10.018

Erum, N., Hussain, S. (2019). Corruption, natural resources and economic growth: Evidence from OIC countries. *Resources Policy*, 63, 101429, https://doi.org/10.1016/j.resourpol.2019.101429

GFN (2023). Global Footprint Network. *Footprintnetwork.org* [online]. Available at: https://data.footprintnetwork.org

Haseeb, A., Xia, E., Saud, S., et al. (2019). Does information and communication technologies improve environmental quality in the era of globalization? An empirical analysis. *Environmental Science and Pollution Research*, 26, 8594–8608, https://doi.org/10.1007/s11356-019-04296-x

Haseeb, A., Xia, E., Saud, S., et al. (2023). Unveiling the liaison between human capital, trade openness, and environmental sustainability for BRICS economies: Robust panel-data estimation. *Natural Resources Forum*, 47(2), 229–256, https://doi.org/10.1111/1477-8947.12277

ICRG (2023). International Country Risk Guide. *Prsgroup.com* [online]. Available at: https://www.prsgroup.com/explore-our-products/international-country-risk-guide/

Khan, A., Muhammad, F., Chenggang, Y., et al. (2020). The impression of technological innovations and natural resources in energy-growth-environment nexus: A new look into BRICS economies. *Science of The Total Environment*, 727, 138265, https://doi.org/10.1016/j.scitotenv.2020.138265

Khan, U., Khan, A. M., Khan, M. S., et al. (2022). Are the impacts of renewable energy use on load capacity factors homogeneous for developed and developing nations? Evidence from the G7 and E7 nations. *Environmental Science and Pollution Research*, 30, 24629–24640, https://doi.org/10.1007/s11356-022-24002-8

Li, M., Ahmad, M., Fareed, Z., et al. (2021). Role of trade openness, export diversification, and renewable electricity output in realizing carbon neutrality dream of China. *Journal of Environmental Management*, 297, 113419, https://doi.org/10.1016/j.jenvman.2021.113419

Liu, X., Olanrewaju, V. O., Agyekum, E. B., et al. (2022). Determinants of load capacity factor in an emerging economy: The role of green energy consumption and technological innovation. *Frontiers in Environmental Science*, 10, 1–11, https://doi.org/10.3389/fenvs.2022.1028161

Murshed, M., Elheddad, M., Ahmed, R., et al. (2022). Foreign Direct Investments, Renewable Electricity Output, and Ecological Footprints: Do Financial Globalization Facilitate Renewable Energy Transition and Environmental Welfare in Bangladesh? *Asia-Pacific Financial Markets*, 29, 33–78, https://doi.org/10.1007/s10690-021-09335-7

Murshed, M., Rahman, M. A., Alam, M. S., et al. (2021). The nexus between environmental regulations, economic growth, and environmental sustainability: linking environmental patents to ecological footprint reduction in South Asia. *Environmental Science and Pollution Research*, 28, 49967–49988, https://doi.org/10.1007/s11356-021-13381-z

OECD (2022). Patents on environment technologies (indicator). Paris: Organisation for Economic Co-operation and Development. Available at: https://doi.org/10.1787/fff120f8-en

Omojolaibi, J. A., Nathaniel, S. P. (2022). Assessing the potency of environmental regulation in maintaining environmental sustainability in MENA countries: An advanced panel data estimation. *Journal of Public Affairs*, 22(3), https://doi.org/10.1002/pa.2526

OWD (2022). Per capita electricity generation from renewables. *Ourworldindata.org* [online]. Available at: https://ourworldindata.org/grapher/renewable-electricity-per-capita

Ozturk, I., Al-Mulali, U., Solarin, S. A. (2019). The control of corruption and energy efficiency relationship: an empirical note. *Environmental Science and Pollution Research*, 26, 17277–17283, https://doi.org/10.1007/s11356-019-05016-1

Pata, U. K. (2021). Do renewable energy and health expenditures improve load capacity factor in the USA and Japan? A new approach to environmental issues. *European Journal of Health Economics*, 22, 1427–1439, https://doi.org/10.1007/s10198-021-01321-0

Pata, U. K., Isik, C. (2021). Determinants of the load capacity factor in China: A novel dynamic ARDL approach for ecological footprint accounting. *Resources Policy*, 74, 102313, https://doi.org/10.1016/j.resourpol.2021.102313

Pata, U. K., Kartal, M. T. (2022). Impact of nuclear and renewable energy sources on environment quality: Testing the EKC and LCC hypotheses for South Korea. *Nuclear Engineering and Technology*, 55(2), 587–594, https://doi.org/10.1016/j.net.2022.10.027

Pellegrini, L., Gerlagh, R. (2006). Corruption, democracy, and environmental policy: An empirical contribution to the debate. *Journal of Environment and Development*, 15(3), 332–354, https://doi.org/10.1177/1070496506290960

Peng, G., Meng, F., Ahmed, Z., et al. (2022). Economic growth, technology, and CO2 emissions in BRICS: Investigating the non-linear impacts of economic complexity. *Environmental Science and Pollution Research*, 29, 68051–68062, https://doi.org/10.1007/s11356-022-20647-7

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

Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross Section Dependence. *Journal of Applied Econometrics*, 22(2), 265–312, https://doi.org/10.1002/jae.951

Qin, L., Raheem, S., Murshed, M., et al. (2021). Does financial inclusion limit carbon dioxide emissions? Analyzing the role of globalization and renewable electricity output. *Sustainable Development*, 29(6), 1138–1154, https://doi.org/10.1002/sd.2208

Qin, Z., Ozturk, I. (2021). Renewable and non-renewable energy consumption in BRICS: Assessing the dynamic linkage between foreign capital inflows and energy consumption. *Energies*, 14(10), 2974, https://doi.org/10.3390/en14102974

Ren, Y. S., Ma, C. Q., Apergis, N., et al. (2021). Responses of carbon emissions to corruption across Chinese provinces. *Energy Economics*, 98, 105241, https://doi.org/10.1016/j.eneco.2021.105241

Salahuddin, M., Alam, K., Ozturk, I., et al. (2017). The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO2 emissions in Kuwait. *Renewable and Sustainable Energy Reviews*, 81(2), 2002–2010, https://doi.org/10.1016/j.rser.2017.06.009

Salman, M., Zha, D., Wang, G. (2022). Indigenous versus foreign innovation and ecological footprint: Dynamic threshold effect of corruption. *Environmental and Sustainability Indicators*, 14, 100177, https://doi.org/10.1016/j.indic.2022.100177

Shang, Y., Razzaq, A., Chupradit, S., et al. (2022). The role of renewable energy consumption and health expenditures in improving load capacity factor in ASEAN countries: Exploring new paradigm using advance panel models. *Renewable Energy*, 191, 715–722, https://doi.org/10.1016/j.renene.2022.04.013

Siche, R., Pereira, L., Agostinho, F., et al. (2010). Convergence of ecological footprint and energy analysis as a sustainability indicator of countries: Peru as case study. *Communications in Nonlinear Science and Numerical Simulation*, 15(10), 3182–3192, https://doi.org/10.1016/j.cnsns.2009.10.027

Sinha, A., Shah, M. I., Sengupta, T., et al. (2020). Analyzing technology-emissions association in Top-10 polluted MENA countries: How to ascertain sustainable development by quantile modeling approach. *Journal of Environmental Management*, 267, 110602, https://doi.org/10.1016/j.jenvman.2020.110602

Tang, T., Shahzad, F., Ahmed, Z., et al. (2022). Energy transition for meeting ecological goals: Do economic stability, technology, and government stability matter? *Frontiers in Environmental Science*, 10, 1–13, https://doi.org/10.3389/fenvs.2022.955494

UN (2021). The 17 Goals. *SDGS.UN.org* [online]. Available at: https://sdgs.un.org/goals

Wang, H., Wei, W. (2020). Coordinating technological progress and environmental regulation in CO2 mitigation: The optimal levels for OECD countries & emerging economies. *Energy Economics*, 87, 104510, https://doi.org/10.1016/j.eneco.2019.104510

Wang, Z., Danish, Zhang, B., et al. (2018). The moderating role of corruption between economic growth and CO2 emissions: Evidence from BRICS economies. *Energy*, 148, 506–513, https://doi.org/10.1016/j.energy.2018.01.167

Wenbo, G., Yan, C. (2018). Assessing the efficiency of China's environmental regulation on carbon emissions based on Tapio decoupling models and GMM models. *Energy Reports*, 4, 713–723, https://doi.org/10.1016/j.egyr.2018.10.007

Westerlund, J. (2008). Panel cointegration tests of the Fisher effect. *Journal of Applied Econometrics*, 23(2), 193–233, https://doi.org/10.1002/jae.967

WMO (2021). *Atlas of Mortality and Economic Losses From Weather, Climate and Water Extremes*. Geneva: World Meteorological Organization. Available at: https://public-old.wmo.int/en/resources/atlas-of-mortality

World Bank (2023). World Development Indicators. World Bank. Washington DC.

Xu, D., Salem, S., Awosusi, A. A., et al. (2022). Load Capacity Factor and Financial Globalization in Brazil: The Role of Renewable Energy and Urbanization. *Frontiers in Environmental Science*, 9, 1–13, https://doi.org/10.3389/fenvs.2021.823185

Zaidi, S. A. H., Hussain, M., Uz Zaman, Q. (2021). Dynamic linkages between financial inclusion and carbon emissions: Evidence from selected OECD countries. *Resources, Environment and Sustainability*, 4, 100022, https://doi.org/10.1016/j.resenv.2021.100022

Zhang, K., Xu, D., Li, S. (2019). The impact of environmental regulation on environmental pollution in China: an empirical study based on the synergistic effect of industrial agglomeration. *Environmental Science and Pollution Research*, 26, 25775–25788, https://doi.org/10.1007/s11356-019-05854-z

Zubi, G., Dufo-López, R., Pasaoglu, G., et al. (2016). Techno-economic assessment of an off-grid PV system for developing regions to provide electricity for basic domestic needs: A 2020–2040 scenario. *Applied Energy*, 176, 309–319, https://doi.org/10.1016/j.apenergy.2016.05.022