Does Geopolitical Fragmentation Affect Clean Energy Generation? Panel Evidence from BRICS Countries

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Abstract

The geopolitical fragmentation has been the center of much attention in the science of empirical economics for a few years. Especially after the 2008 financial crisis, the fragmentation in the world economy has risen significantly due to the various economic and political conflicts in the world. Therefore, the practitioners have started to investigate the impact of geopolitical fragmentation on economic variables. However, its effect on energy variables was surprisingly neglected by researchers. For this purpose, the current study aims to explore the impact of geopolitical fragmentation on clean energy generation for five emerging economies, namely, Brazil, Russia, India, China, and South Africa. This relationship is tested through novel panel data techniques. The empirical results proved that there is a cointegration relationship between clean energy generation, geopolitical fragmentation, per capita income, and financial development for the period 1989-2021. Our results suggest that geopolitical fragmentation leads to a rise in clean energy generation in China, while it has a negative impact on it in South Africa. These results may help policymakers to design better energy policies for the following periods.

Keywords: BRICS countries, clean energy generation, financial development, geopolitical fragmentation, panel data analysis

JEL Codes: C33, G20, Q43

Jeopolitik Parçalanma Temiz Enerji Üretimini Etkiliyor mu? BRICS Ülkelerinden Panel Veri Bulguları

Öz

Bu çalışma, jeopolitik parçalanmanın BRICS ülkelerinde temiz enerji üretimi üzerindeki etkisini incelemektedir. Büyük Resesyon sonrasında uluslararası ekonomik düzenin parçalı bir yapıya yönelmesi, enerji dönüşümünün belirleyicilerini yeniden tartışmaya açmıştır. Kişi başına gelir ve finansal gelişmenin de modele dahil edildiği analizde, panel veri yöntemleri kullanılarak hem ortak hem de ülkeye özgü katsayılar tahmin edilmekte; yatay kesit bağımlılığı ve eğim heterojenliği dikkate alınmaktadır. Bulgular, kişi başına gelirin Brezilya, Rusya ve Çin'de temiz enerji üretimini artırdığını göstermektedir. Toplam finansal gelişme endeksinin temiz enerji üretimi üzerindeki etkisi Brezilya ve Güney Afrika'da pozitiftir. Jeopolitik parçalanma ise yalnızca Çin'de temiz enerji üretimini artırmaktadır. Bu sonuçlar, söz konusu değişkenlerin temiz enerji üretimi üzerindeki etkisinin BRICS ülkeleri arasında tördeş olmadığını ve politika tasarımında ülkelerin yapısal farklılıklarının dikkate alınması gerektiğini ortaya koymaktadır. Çalışma politika yapıcılar için üç temel çıkarım sunmaktadır: ekonomik büyümeye yönelik politikaların sürdürülmesi, gerekli kamu müdahalesiyle sağlıklı bir finansal sistemin kurulması ve jeopolitik risklerin enerji arz güvenliği açısından gözetilmesi.

Anahtar Kelimeler: BRICS ülkeleri, temiz enerji üretimi, finansal gelişme, jeopolitik parçalanma, panel veri analizi

JEL Kodları: C33, G20, Q43

1. Introduction

Following the Great Recession, the international economy has started to shift from globalization to fragmentation recently. Several economic and political issues worldwide have contributed to this fragmentation, including Brexit, the Russia-Ukraine War, and the US-China trade wars, among others (Fernández-Villaverde et al., 2024). Geopolitical fragmentation not only affects the economic indicators but also may influence the energy policy of the countries. This investigation aims to examine the impact of geopolitical fragmentation on clean energy generation for BRICS countries (Brazil, Russia, India, China, and South Africa) during the period 1989-2021 to shed light on this proposition.

Clean energy generation refers to electricity produced from renewable and nuclear sources. While these technologies entail some environmental costs, such as construction impacts and nuclear waste, their damage is considerably lower than that of fossil fuels. Consequently, countries concerned with sustainability often prioritize clean energy to diversify their energy mix, reduce exposure to energy price shocks, and mitigate the risks of supply disruptions or embargoes.

The relationship between globalization and renewable energy has been widely investigated in empirical literature. For instance, Gozgor et al. (2020) found that economic globalization increases renewable energy consumption in OECD countries, while Ghazouani (2022) reports a time-varying but ultimately positive effect of globalization on renewable energy. Extending this literature, Nan et al. (2023) indicated that political and social globalization raises renewable energy transition in spatial spillovers. Zhang et al. (2021) find that trade openness exerts nonlinear but overall positive effects on renewable energy use. In addition, Zuo and Majeed (2024) revealed that rising trade uncertainty constrains renewable energy deployment in China. By contrast, the emerging literature on geopolitical risks points to significant constraints on renewable energy. Zhao et al. (2023) reported that heightened geopolitical risks reduce renewable energy demand in OECD countries. Similarly, Ren et al. (2024) found that geopolitical tensions weaken the convergence of renewable energy consumption, while Depraiter and Goutte (2025) reveal that geopolitical risks associated with critical minerals amplify volatility in clean energy investments. To the best of the author’s knowledge, however, no study has investigated the impact of geopolitical fragmentation on renewable energy. This study addresses this gap by providing novel empirical evidence on its implications for clean energy generation.

In this paper, the long-run relationship between variables is tested through the panel cointegration test of Westerlund and Edgerton (2007), which accounts for cross-sectional dependency. Besides, the long-term coefficients are estimated via the Augmented Mean Group (AMG) estimator developed by Eberhardt and Teal (2010).

This paper consists of four main sections. The second part of this study proceeds as follows: introduction of data, models, and methods. The third section presents empirical findings and discusses them clearly. The last section concludes the study, including policy implications and suggestions for further research.

2. Data, Models, and Methods

This study utilizes an annual dataset comprising six variables and three models for the BRICS countries, spanning the period 1989-2021. The models and variables are introduced below:

Table 1. Data and Models

Variables	Abbreviations	Forms	Sources
Clean energy generation per cap	*ceg*	Natural Logarithm	Energy Institute (2025)
Financial development index	*fide*	Natural Logarithm	IMF (2025)
Financial institutions index	*fiin*	Natural Logarithm	IMF (2025)
Financial market index	*fima*	Natural Logarithm	IMF (2025)
GDP per capita (constant 2015 US$)	*gdp*	Natural Logarithm	World Bank (2025)
Geopolitical Fragmentation Index	*gefr*	Level	Fernández-Villaverde et al. (2024)
Models	**Variables**		
Model 1	*ceg = f(fide, gdp, gefr)*		
Model 2	*ceg = f(fiin, gdp, gefr)*		
Model 3	*ceg = f(fima, gdp, gefr)*		

In order to detect these cross-sectional features among variables, two cross-section dependence tests proposed by Breusch and Pagan (1980) and Pesaran (2021) are utilized.

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^{2} \quad \chi^{2}_{N(N-1)/2)} \tag{1}$$

In equation (1), Breusch and Pagan (1980) cross section dependency test, $\hat{\rho}_{ij}$ is the correlation coefficient between the residuals obtained from each regression. When N (cross section) is constant and time (T) goes to infinity, the null hypothesis indicates that there is no correlation between the residuals.

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T \hat{\rho}_{ij}^{2} - 1\right) N(0,1) \qquad (2)$$

In equation (2), cross section dependency test introduced by Pesaran (2021) employs the Lagrange Multiplier (LM) when time (T) goes to infinity and then N (cross section) goes to infinity. The null hypothesis for this test is that there is no correlation among residuals.

Before the examination of long run cointegration relationship among variables, the stationarity characteristics of the data should be investigated whether the series are stationary or not. In order to determine whether the series are stationary or not, panel unit root test introduced by Bai and Ng (2004) is utilized.

$$X_{¿} = c_i + b_i t + \lambda_i F_t + e_{¿} \qquad (3)$$

$$\Delta X_{¿} = \beta_i + \lambda_i \Delta F_t + \Delta e_{¿} \qquad (4)$$

$$\Delta X_{¿} - \overline{\Delta X}_i = \lambda_i \left(\Delta F_t - \overline{\Delta F} \right) + \left(\Delta e_{¿} - \overline{\Delta e}_i \right) \qquad (5)$$

$$x_{¿} = \lambda_i f_t + z_{¿} \qquad (6)$$

Many macroeconomic and financial time series exhibit unit root behavior, indicating non-stationarity in their levels. The inclusion of such non-stationary series in estimation can result in spurious regression, leading to misleading inferences. A conventional solution for this problem is to take the first difference of the series. However, this transformation reduces the sample size and may eliminate valuable information regarding the long-run equilibrium relationship among variables. To address this limitation, Engle and Granger (1987) introduced the concept of cointegration. According to this method, if two series are integrated of order one, I(1), but a linear combination of them is stationary, then a stable long-term relationship exists between them. This approach allows researchers to explore long-run associations between non-stationary series without resorting to first differencing, thereby preserving essential information in the series (Baltagi, 2008; Asteriou and Hall, 2011). First generation panel cointegration tests do not consider the cross-sectional dependence among variables, and this leads to display potential cointegration relationship which actually does not exist in the model. Due to this reason, in this research we apply panel cointegration tests with cross section dependence proposed by Westerlund and Edgerton (2007).

The panel cointegration test of Westerlund and Edgerton (2007) is based on McCoskey and Kao (1998) with Lagrange Multiplier by accounting for the cross-section dependency. Westerlund and Edgerton (2007) defines the model as follows:

$$y_{¿}=\delta_i^{'}d_t+b_i^{'}x_{¿}+\varepsilon_{¿} \tag{7}$$

where d_t define as $d_t=(1,t)'$ for constant and trend model, $x_{¿}$ is a m-dimensional vector of regressors, which are assumed to be pure random walk processes. The disturbance $\varepsilon_{¿}$has the following decomposition:

$$\varepsilon_{¿}=u_{¿}+v_{¿}\, with\, v_{¿}=\sum_{j=1}^{t}\eta_{ij} \tag{8}$$

where η_{ij} is an independent and identically distributed (i.i.d.) process with zero mean and variance $var(\eta_{ij})=\sigma_i^2$.

The panel cointegration test of Westerlund and Edgerton (2007) is based on McCoskey and Kao (1998) with the Lagrange Multiplier by accounting for cross-section dependency. The null hypothesis of Westerlund and Edgerton (2007) panel cointegration test is that there is long-run cointegration relationship among variables, while under alternative hypothesis is that there is no cointegration between series, which is equivalent to testing $H_0:\sigma_i^2=0$ for all i against $H_1:\sigma_i^2>0$ for some i. This hypothesis can be tested using the following test statistics:

$$LM_N^{+¿=\frac{1}{NT^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\omega}_i^{-2}S_{¿}^{2}¿} \tag{9}$$

where $S_{¿}$ is the partial sum process of $\hat{\varepsilon}_{¿}$, the fully modified estimate of $\varepsilon_{¿}$, and $\hat{\omega}_i^2$ is the estimated long-run variance of $u_{¿}$ conditional on $\Delta x_{¿}$.

Finally, the long-run relationship between variables is estimated by the AMG estimator of Eberhardt and Teal (2010). Besides, the slope homogeneity test, developed by Pesaran and

Yamagata (2008), is used to determine whether the long-term coefficients of the model are homogenous or heterogenous.

3. Empirical Results and Discussion

First, the cross-section dependence test for the series is employed to determine which unit root test is most suitable for our dataset. The empirical results displayed in Table 2 show that all of the series suffer from the cross-section dependence issue; therefore, we need to use the second-generation unit root test in this study.

Table 2. Cross-Section Dependence Tests Results

Variables	LM	p-value	CD_{LM}	p-value
ceg	233.4435***	0.0000	49.96347***	0.0000
fide	180.8169***	0.0000	38.19582***	0.0000
fiin	250.6743***	0.0000	53.81642***	0.0000
fima	130.8943***	0.0000	27.03278***	0.0000
gdp	260.5650***	0.0000	56.02805***	0.0000
gefr	330.0000***	0.0000	71.55418***	0.0000
Model 1	41.91148***	0.0000	7.135624***	0.0000
Model 2	88.64964***	0.0000	17.58659***	0.0000
Model 3	35.00525***	0.0001	5.591344***	0.0000

Note: *** indicates 1% level of significance.

According to the panel unit root test proposed by Bai and Ng (2004), all the series are nonstationary at their level values, while they have mean-reverting behavior at their first differences, I(1) (see Table 3). So, one can say that the effects of any shocks to these series are permanent, not transitory.

Table 3. Panel Unit Root Test Results

Variables	Test Statistics	p-value	Variables	Test Statistics	p-value
ceg	-0.70428	0.48126	Δ*ceg*	10.42628***	0.00000
fide	-0.99572	0.31939	Δ*fide*	6.539018***	0.00000
fiin	1.60748	0.10795	Δ*fiin*	13.39111***	0.00000

Variables	Test Statistics	p-value	Variables	Test Statistics	p-value
fima	-0.41808	0.67589	Δ*fima*	5.293769***	0.00000
gdp	-0.45060	0.65228	Δ*gdp*	9.508878***	0.00000
gefr	-1.63054	0.10299	Δ*gefr*	8.637381***	0.00000

Note: ***, **, * indicates 1% level of significance.

Since all the series are nonstationary at the level, the long-run relationship between variables can be investigated through the panel cointegration tests. According to the cross-section dependence test for the model (see Table 2), the second-generation panel cointegration tests are proper for the analysis of this study.

This study conducts the panel cointegration test of Westerlund and Edgerton (2007) to reveal the long-run relationship between variables. The empirical results presented in Table 4 show that we cannot reject the null hypothesis of cointegration in panel data. This means that the abovementioned series move together in the long-run.

Table 4. Panel Cointegration Test Results

Models	LM Statistics	Asymptotic p-value	Bootstrap p-value
Model 1	1.096	0.137	0.995
Model 2	1.070	0.142	0.980
Model 3	0.938	0.174	0.999

Note: *** indicates 1 % level of significance.

The long-run coefficients of the variables are estimated through the second-generation AMG estimator. Table 6 presents the country-specific coefficients for all the models because of the presence of slope heterogeneity across countries (see Table 5 below).

Table 5. Slope Homogeneity Test Results

Models	Delta	Delta Adjusted
Model 1	14.182***	15.396***
Model 2	13.679***	14.850***
Model 3	14.012***	15.212***

Note: *** indicates 1% level of significance.

Table 6. AMG Estimation Results

Countries	***constant***	***gdp***	***fide***	***gefr***
Brazil	-16.620***	0.387***	0.133*	-0.026
Russia	-15.041***	0.210***	-0.001	0.032
India	-19.777***	0.475	-0.407	0.032
China	-27.635***	1.597***	-0.438	0.205***
South Africa	-15.880***	0.200	0.593**	-0.129*
Panel	-18.991***	0.574**	-0.024	0.022
Countries	***constant***	***gdp***	***fiin***	***gefr***
Brazil	-16.712***	0.386***	0.084	-0.041
Russia	-14.346***	0.155***	0.124	-0.010
India	-22.166***	1.009**	0.337	0.077
China	-24.259***	1.307***	0.680**	0.126
South Africa	-19.128***	0.459	-0.340	-0.339***
Panel	-19.322***	0.663***	0.177	-0.037
Countries	***constant***	***gdp***	***fima***	***gefr***
Brazil	-16.857***	0.425***	0.136**	-0.022
Russia	-15.062***	0.213***	-0.000	0.025
India	-18.929***	0.379	-0.233	0.008
China	-28.869***	1.798***	-0.346**	0.132*
South Africa	-18.510***	0.490	0.304***	-0.177**
Panel	-19.645***	0.661**	-0.027	-0.006

Note: ***, **, and * indicate 1%, 5%, and 10% levels of significance, respectively.

The empirical results demonstrate that per capita GDP has a positive impact on per capita cleaner energy generation in Brazil, Russia, and China for all three models. Besides, this result is valid for India only for Model 2. This means that an increase in income level causes a rise in environmental consciousness in these countries. During the economic development process, these emerging economies have started to exit from fossil fuels (such as coal, oil, and natural gas) and begin to use cleaner energy sources such as wind, solar, hydropower, geothermal, and nuclear energy.

On the finance side, it is seen that an increase in the financial development level of countries has a positive contribution to the clean energy generation in Brazil and South Africa for the period examined. At the disaggregated level, a rise in the financial institutions index, meaning better performance of financial institutions (such as bank performances), leads to more clean energy generation in China. This result can be explained by the fact that firms invested in the renewable energy and nuclear energy sectors benefit from the development of financial institutions in the country, such as financial depth, financial access, and financial efficiency. In this case, these firms can borrow credit from financial intermediaries and set up or extend their operations more easily. Lastly, more development in financial markets increases clean energy production in Brazil and South Africa, while it has a negative impact on it in China. Advancements in stock market indicators, such as turnover ratio, market capitalization of firms, stocks traded to GDP, and so on, cause a better financial environment in the countries. Superior financial market development may encourage more firms to make an initial public offering, and these companies (including clean energy firms) can extend their operations. The negative coefficient for China can be explained by the fact that the politicization of stock markets. For instance, the interests of the Chinese government are closely reflected in the stock market, and the government uses the stock market to support state-owned enterprises (Zhang, 2024).

Lastly, the impact of geopolitical fragmentation on clean energy generation is investigated for the BRICS countries, and the empirical findings are displayed in the last column of Table 6. It is seen that the fragmentation increases the clean energy production in the Chinese economy. The recent economic and political tensions between the USA and China, the different perspectives on economic systems between the Western countries and China, and conflicts in the Middle Eastern countries may have increased the energy concerns in China. Therefore, China increased its renewable and nuclear energy capacity significantly in recent decades. Contrarily, its impact is negative for South Africa for the period studied. Since the relationship between South Africa and the Western bloc is tighter, one can say that less geopolitical fragmentation, meaning a more globalized economy, has a positive impact on clean energy generation. This close relationship with the capitalized countries creates investment opportunities for the energy sector. For instance, about 60% of South Africa's wind and solar energy capacity is financed by foreign investment (Bridgewater Insights, 2025).

Panel AMG results are insignificant considering geopolitical fragmentation, but country estimates reveal heterogeneity—positive in China and negative in South Africa—showing that the average masks divergent BRICS experiences. Geopolitical fragmentation promotes clean energy in Brazil and India, where supportive policies prevail, but reduces diversification in resource-dependent Russia. China sustains growth through state-led policies, while South Africa's coal reliance hinders transition. These contrasts show that panel averages mask country-specific dynamics shaped by institutions and resources.

4. Conclusion

This paper found that per capita income, financial development, and geopolitical fragmentation have a significant impact on clean energy production for BRICS countries; however, their impacts differ across countries:

- Income per capita increases clean energy generation in Brazil, Russia, and China.
- Aggregate financial development has a positive impact on clean energy generation in Brazil and South Africa.
- Geopolitical fragmentation leads to a rise in clean energy generation only for China.

The following are the main policy implications of our study: (i) since the economic development process increases environmental awareness among economic agents, governments need to conduct policies oriented towards economic growth, (ii) policymakers should set up a sound financial system only with necessary government intervention, and (iii) they need to consider their interactions with other countries because their actions may affect their clean energy performance through geopolitical fragmentation.

Further research can focus on different countries, regions, or groups for their analysis. Also, other types of fragmentation can be taken into account, such as trade, financial, mobility, and political ones. In addition, various types of bloc fragmentation might be considered, such as the US-EU bloc, the China-Russia bloc, and other blocs.

Declarations

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Data availability. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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