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RESEARCH ARTICLE

Economic growth, technology, and CO_2 emissions in BRICS: Investigating the non-linear impacts of economic complexity

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Abstract
Upgrading economic structures and producing less pollution-intensive goods are indispensable for achieving Sustainable Development Goals (SDGs) in BRICS (Brazil, Russia, India, China, and South Africa) that produce 41% of global CO_2 emissions. Economic complexity (ECC), which measures the sophistication of productivity and economic structure, has important environmental repercussions. Theoretically, the environmental impacts of economic complexity at higher levels and lower levels of complexity vary from each other. However, the majority of previous studies have overlooked these theoretical underpinnings while assessing the environmental repercussions of economic complexity. In addition, technological competencies are necessary to boost the economic complexity levels. Accordingly, this study uncovers the non-linear effects of economic complexity on CO_2 emissions including technology, population density, and economic growth in a STIRPAT model. To this end, the panel data from 1992 to 2018 is analyzed using the Continuously Updated Fully Modified method (CuP-FM) in the context of BRICS. The long-run results uncovered that CO_2 emissions intensify at a lower level of economic complexity. On the flip side, a higher level of economic complexity is beneficial in mitigating CO_2 in BRICS. Hence, the economic complexity and CO_2 connections follow an inverted U-shaped curve. The results also disclosed that expanding the level of technology lessens CO_2 and stimulates the quality of the environment. Further, population density and economic growth are evidenced to intensify CO_2. Moreover, economic complexity and technology Granger cause CO_2. Lastly, strategies are directed in the context of Sustainable Development Goals 9 and 13 to control CO_2 emissions by upgrading technology and products complexity.

Keywords Technology · CO_2 emissions · Environmental Sustainability · Economic complexity · Innovation

Introduction

Economic growth is necessary to decrease poverty, improve the standard of life, and stimulate human wellbeing. However, one of the negative externalities of development is human-induced CO_2 emissions, which are believed to trigger climate change and environmental deterioration. Accordingly, global CO_2 emissions have expanded by more than 50% since the start of the industrial revolution (IEA 2021). Also, various weather extremes, such as floods, droughts, heatwaves, and cyclones, are evident across the globe (IPCC 2021). The world has realized that combined efforts are required to mitigate environmental adversities and ensure sustainable growth.

In this context, decades of collaboration between the United Nations (UN) and countries resulted in the adoption of Agenda 2030 based on seventeen important SDGs (UN 2021). Among these targets, SDG 13 calls for taking steps

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to control global climate change and stimulating mitigation activities to reduce the adverse effects of climate change (Xue et al. 2022). Given that most of the emissions are generated by the combustion of fossil energy for economic development, SDG 9, which demands sustainable industrialization based on innovation, is critically important to build modern, efficient, and green technologies. Innovation is an important element for increasing productivity and economic progress, and advanced technology developed by innovation can reduce emissions due to energy efficiency and energy transition (Kihombo et al. 2021a).

In addition to technology, other factors can also affect climate actions. Among such factors, economic complexity (ECC) has emerged as a vital driver of environmental quality in recent literature. ECC denotes a production structure based on knowledge and skills which produces substantial output (Can and Gozgor 2017). ECC index is a ranking of nations in terms of sophisticated products in their export baskets, and thereby it covers the production dynamics of nations by considering capabilities (Ahmed et al. 2021). Generally, ECC is believed to influence environmental quality differently at various levels of economic complexity. In this context, less developed nations with a low ECC try to acquire economic growth by improving the agriculture sector, and thus, energy usage and environmental issues are generally low at this stage. However, with a rise in industrialization, advanced complexed products are manufactured. But, the path toward manufacturing complex products gives rise to energy-intensive goods, for instance, textile, metal, and cement, at early stages (Doğan et al. 2019). Hence, ECC poses threats to environmental quality at this stage. Nevertheless, the situation reverses with a rise in development, as societies with more environmental preferences tend to specialize in producing complex and innovative products and thereby dump high resource-intensive goods from export baskets (Can and Gozgor 2017). Alongside, the increase in innovation with the development improves economic structure resulting in more efficiency and less energy utilization. Thus, ECC can benefit the environment and decrease CO_2 at this stage.

Considering these arguments, it can be expected that ECC may drive CO_2 at early stages, but higher levels of ECC can benefit the environment. However, empirical evidence on this subject is mixed. For instance, Neagu (2020) uncovered that ECC boosts environmental deterioration in the most complex nations. Likewise, in the USA, Shahzad et al. (2021) found that ECC harms environmental quality. Conversely, (Ahmed et al. 2021) illustrated that ECC mitigates environmental problems in the developed group of seven countries. The main reason behind these inclusions findings could be that most of these investigations believed that ECC poses a linear effect on environmental deterioration; however, the theoretical underpinnings indicate that this relationship can be non-linear. Further, Chu (2021) suggests that ECC poses non-linear effects on environmental deterioration as higher levels of ECC lessen environmental issues compared to the low levels of ECC that augment environmental problems. Thus, there is a need to revisit the environmental impacts of ECC by considering the potential non-linear effects of ECC.

Previous empirical investigations on ECC and CO_2 connection present equivocal findings. Moreover, as discussed above, the theoretical background suggests that different levels of ECC may impact CO_2 differently. In this context, the objective of this study is to assess the non-linear effects of ECC on CO_2 in BRICS, including technology, population density, and economic growth from 1992 to 2018. The selection of BRICS as a sample for this study is motivated by the fact that these five nations (India, Brazil, Russia, China, and South Africa) constitute 23% of global GDP and generate 41% of global CO_2 emissions (Khan et al. 2020a). The nations like Russia, India, China, and Brazil are ranked in the list of the top seven CO_2 emitting countries (Ahmad et al. 2022a, b). The environmental challenges posed by BRICS are far more severe compared to the developed world. This is because CO_2 in BRICS intensified from 27 to 42% from 1990 to 2018, while for the same period, in the developed group of European Union nations, CO_2 decreased from 40 to 25% (Zeng and Yue 2021). Given that BRICS experienced 6.5% of annual growth (on average) over the past decade (Khan et al. 2020a), these developing nations need to upgrade their existing technologies and build new innovative technology to decrease adverse externalities of development. Alongside, the production of sophisticated goods and dumping resource-intensive goods will be vital for BRICS to achieve SDGs. Thus, this work evaluates the economic complexity, technology, and CO_2 nexus considering the possible non-linear effect of ECC for better environmental policies.

Against this backdrop, this paper extends the literature and makes the following contributions. First, it uncovers the non-linear impact of economic complexity on CO_2 in BRICS countries, including technology, population density, and economic growth in the model. This work is a pioneer effort to probe the non-linear effects of ECC on CO_2 in the context of BRICS. We included technology in the model since producing complex product demands sophisticated technology. Second, the popular long-run estimator (CuP-FM) is applied because it can tackle common panel data issues like endogeneity, cross-sectional dependence (CSD), residual correlation, fractional integration, and heteroscedasticity. Third, the non-linear influence of ECC on CO_2 is explored by using the STIRPAT model. This reliable model is famous for capturing the environmental impacts of variables by avoiding omitted variable bias problems. Moreover, the empirical evidence is verified using the CuP-BC test. This investigation will be expedient in designing environmental policies, particularly keeping in view SDGs 13 and 9.

Literature review

In recent decades, empirical studies on the economic performance of nations, innovation, technology, and environmental pollution are increasing (Muhammad and Long 2020; Chi et al. 2021; Ahmad et al. 2022b). Many empirical studies probed ECC and CO_2 nexus with inconclusive findings. The detail of such studies is discussed below.

The innovative work of Can and Gozgor (2017) probed the CO_2 and ECC nexus in France. They concluded that ECC lessens CO_2. The panel study of Doğan et al. (2019) also supported this conclusion and validated that ECC alleviates emissions in nations with high income. However, they add to these findings by uncovering the adverse effects of ECC on the environment in middle- and low-income nations. From the estimates of these two investigations, it seems that higher levels of ECC are beneficial for the quality of the environment. However, the conclusions of Neagu (2020) for most complex nations refuted the earlier works of Doğan et al. (2019) and Can and Gozgor (2017), as it revealed that ECC intensifies environmental deterioration. Similarly, Shahzad et al. (2021) disclosed that ECC raises the CO_2 levels in the USA. Their empirical investigation did not uncover the environmental benefits of ECC in a highly developed nation. Thus, their work also synchronizes with the research of Neagu (2020). Likewise, Martins et al. (2021) suggested that CO_2 emissions raise with an increase in ECC in 7 nations with the highest ECC. Also, Wan et al. (2022) documented that increasing economic complexity minimizes environmental deterioration in India.

Conversely, Boleti et al. (2021) evidenced that boosting ECC is fruitful for enhancing environmental performance irrespective of income level. However, ECC expands emissions levels in 88 nations. However, Doğan et al. (2020) uncovered that ECC alleviates CO_2 in the developed group of nations. Likewise, Ahmed et al. (2021) evidenced that ECC lowers CO_2 in the developed group of seven. Thus, enhancing ECC can benefit the environment. In the same vein, He et al. (2021) disclosed that ECC mitigates CO_2 in nations with a high degree of the energy transition. On the flipside, Nathaniel (2021) unveiled that ECC enhances environmental pollution in ASEAN. Similarly, (Adebayo et al. 2022b) revealed that ECC enhances emissions in MINT economies across different quantiles. Likewise, Ahmad et al. (2021) found that ECC expands environmental deterioration by raising EF in emerging nations. However, Lapatinas et al. (2021) somewhat opposes such findings and evidenced that boosting ECC encourages an environmental culture in a nation. In contrast, Yilanci and Pata (2020) disclosed that ECC raises EF and environmental problems in China.

In the context of non-linear impacts of ECC, Chu (2021) suggested that ECC and environmental issues have an inverse U-shaped link in a panel of 118 nations. However, they used ECC instead of economic growth, and ECC differs from the economic growth to a great extent. The omission of economic growth from the model can cause omitted variable bias. Likewise, Pata (2021) evidenced that ECC and ecological footprint (EF) have a non-linear connection. Thus, higher levels of ECC mitigate EF compared to the low values of ECC that enhance EF. Therefore, this connection is similar to an inverted U-shaped curve. This opposes the work of Shahzad et al. (2021) who uncovered environmental deterioration caused by ECC in the USA. Balsalobre-Lorente et al. (2022) revealed an N-shaped and inverted U-shaped linkage between ECC and CO_2 in some PIIGS countries. In addition, Muhammad et al. (2022) unfolded a non-linear U-shaped connection between the industrial structure of the secondary industries and environmental efficiency in the context of developed countries. Yang et al. (2021) illustrated that industrial structure curbs CO_2 in China but its impact varies across cities and sectors.

Technology is vital for expanding ECC levels because producing complex goods require state-of-the-art technology. Upgrading technology is also important to control environmental pollution; however, previous works on technology and environmental pollution connection present different findings. For instance, Khan et al. (2020b) uncovered that technology diminishes pollution in the G7. Thus, upgrading technology can help to achieve carbon neutrality. Likewise, Mensah et al. (2018) illustrated that technology elevates CO_2 in OECD. Similarly, Santra (2017) indicated that technology decreases CO_2 in BRICS. In the APEC context, Wasif et al. (2021) found that technology is useful in controlling CO_2 and increasing the quality of the environment. In the same vein, Kihombo et al. (2021a, b) uncovered that technology lessens environmental problems in the WAME countries. Similarly, Rafique et al. (2020) also uncovered that technology is negatively linked with CO_2 in BRICS.

However, Adebayo et al. (2021c) refuted these findings and illustrated that technological innovation intensifies pollution in Chile. In the N-11 nations, Sinha et al. (2020) also revealed that technology expands environmental deterioration. Likewise, Alvarez-Herranz et al. (2017) documented that innovation in the energy sector boosts air pollution levels in selected OECD nations. Likewise, Awosusi et al. (2022) suggested that technological innovation boosts emissions in BRICS. In contrast, Balsalobre et al. (2015) found that raising research and development and innovation in the energy sector can curb environmental pollution in OECD. Wang et al. (2020a, b) concluded that technology diminishes environmental pollution in N-11 countries. Ahmad et al. (2020) established that technology lessens environmental pollution in emerging groups of nations. Likewise, Zhao et al. (2021) evidenced that technology mitigates CO_2 in a global panel. In the same vein, Adebayo et al. (2021a) indicated that technology lessens CO_2 in South Korea. Similarly, Shahbaz et al. (2020) evidenced that CO_2 lessens due to an increase in technology in China. Likewise, Ahmad et al. (2022a) illustrated that technology is beneficial for environmental quality in BRICS. In Portugal, Adebayo et al. (2021b) found that technology lessens CO_2 and expands environmental quality.

In a nutshell, empirical investigations report increasing or decreasing impacts of ECC on the quality of the environment. It is noteworthy that most studies estimated the linear effects of ECC on CO_2. However, ECC may impact environmental quality differently at a higher level compared to a low level. Thus, it is important to add the quadratic form of ECC and assess the non-linear effects of ECC on CO_2. Besides, technology and environment nexus may vary across nations because energy-intensive technology can raise CO_2, while efficient technology can reduce it. Thus, this study uncovers the non-linear impacts of ECC on CO_2 emissions by including technology in the context of BRICS.

Data and empirical strategy

In this section, the theoretical background, model construction, data, and empirical strategy will be discussed.

Theoretical background and data

This research unveils the non-linear impacts of ECC on CO_2 emissions in BRICS. According to the studies of Doğan et al. (2019) and Ahmed et al. (2021), when countries intend to develop complex goods, they end up producing dirty products, such as textile, metal, and cement, at the early development level, which in turn boost environmental degradation. However, the situation changes with a high development because nations' preferences for a clean environment along with extensive innovation and cleaner technologies enable them to produce less resource-intensive goods and dump dirty products from the export baskets (Can and Gozgor 2017). Thus, high levels of ECC may decrease CO_2, and low levels of ECC may boost CO_2. Therefore, an inverted U-shaped curve between ECC and CO_2 is possible. These arguments provide the foundation to explore the non-linear impact of ECC on CO_2.

Apart from this, environmental pollution is largely connected with the growth of nations (Lin et al. 2021). Therefore, a massive increase of 50% in global emissions took palace from the start of the industrial revolution (IEA 2021). In order to lessen global emissions, it is necessary to adopt more clean energy options but developing clean energy technology is subject to a massive upsurge in technological innovation (Kihombo et al. 2021a). Modern technology is critical to achieving energy efficiency and controlling environmental pollution (Wasif et al. 2021). Additionally, an increase in population density exerts significant pressure on the use of energy and other resources, which in turn enhances CO_2 (Liu et al. 2017).

To assess the non-linear effects of ECC on CO_2, the STIRPAT model, which stands for the Stochastic Impacts by Regression on Population, Affluence, and Technology, is applied. This model is overwhelmingly used to assess various variables' effects on the environment. The equation of this model is as follows.

$$I_t = aP_t^b A_t^c T_t^d \mu_t \tag{1}$$

In this equation, CO_2 captures the environmental impact (I) while technology (T), affluence (A), and population (P) are represented by technological innovation, economic growth, and population density. This model is preferred in environmental studies because it offers a lot of flexibility and the addition of new variables to this model is possible (Ali et al. 2022). Thus, economic complexity and its quadratic form are also added to the STIRPAT model to gauge the non-linear effect of ECC on CO_2. The final model of this study is given below.

$$\left(CO_2\right)_{it} = \delta_0 + \delta_1 Y_{it} + \delta_2 ECC_{it} + \delta_3 ECC_{it}^2 + \delta_4 T_{it} + \delta_5 PD_{it} + \mu_{it} \tag{2}$$

In Eq. 2, CO_2, ECC, ECC^2, T, Y, and PD depict CO_2 emissions (per capita tonnes), economic complexity, economic complexity's square, technology (total resident and non-resident patent applications), economic growth (per capita GDP 2015 constant US \$), and population density, respectively. Further, δ shows the intercept, and the residual term is symbolized by μ. The variables except for the economic complexity index, which has both negative and positive values, are transformed into a natural logarithm to compute reliable findings. The series on CO_2 and ECC came from BP (2021), and OEC (2021), respectively. The ECC index utilized in the study presents the relative rating of countries based on products in their export baskets. The ECC variable represents the productive economic structure because it considers the variations and sophistication of industrial structure for measuring countries' productive structures (Can and Gozgor 2017; Ahmad et al. 2021). According to Hartmann et al. (2017), ECI is a useful measure to capture the degree of knowledge and sophistication levels of the productive structure of various economies.

It is worth mentioning that the ECC data series is available only until 2017; thus, the linear extrapolation approach is used to extend the series for 2018, which is in line with Wang et al. (2019). The data on population density, technology, and economic growth is collected from WDI (2021). The period of investigation from 1992 to 2018 is based on data availability. As the data on ECC and technology are available from 1992 for Russia, so the starting period of 1992 is selected for this research. In addition, the ending period is knotted with the data period of CO_2 and ECC.

Econometric methodology

The interconnection among nations across the world has increased the dependence of countries on each other; however, most of the conventional panel data estimation tests overlook the potential dependence in data. The assumption of independence, which is the foundation of first-generation tests, leads to biased results when datasets are cross-sectionally dependent. To address this problem, it is critical to probe the cross-sectional dependence (CSD) issue before estimating the panel data of BRICS. In this context, the Breusch-Pagan LM test, the Pesran's Scaled LM test, and the CD test of Pesaran (2004) are adopted. The CD is based on the following equation.

$$CDT = \sqrt{\frac{2t}{z(z-1)}}\left(\sum_{i=1}^{z-1}\sum_{j=i+1}^{z}\hat{C}_{ij}\right) \tag{3}$$

where CDT refers to the CD test, t symbolizes time, z represents the size of the sample, and $\hat{C}_{ij}$ denotes pair-wise autocorrelation.

All the methods applied for assessing CSD in BRICS' panel evidenced CSD in data; therefore, unlike the conventional unit root tests, the second-generation methods (i.e., CADF and CIPS) are chosen for unit root testing. This is reasonable to adopt these two methods of Pesaran (2007) since they can reveal the integration level amidst CSD and heterogeneity. The CADF test's equation is as follows:

$$\Delta G_{i,t} = \sigma_i + \varphi_i G_{i,t-1} + \varphi_i \overline{AZ}_{t-1} + \sum_{l=0}^{k}\varphi_{il}\Delta\overline{AZ}_{t-1} + \sum_{l=0}^{k}\varphi_{il}\Delta G_{i,t-1} + \varepsilon_{it} \tag{4}$$

In Eq. 4, the expressions $\overline{AZ}_{t-1}$ and $\Delta\overline{AZ}_{t-1}$ depict cross-sectional average, σ show the intercept, k is lag order, and G indicates the computed variable. The CIPS test differs from this test as the cross-sectional average (referred above) is used to compute the CIPS statistics.

The computed output from both these tests evidenced that variables in the BRICS panel are integrated at various orders, i.e., 1(1) and 1(0). The response variable is integrated at 1(1), and regressors exhibit mixed order of integration; hence, most of the cointegration tests are inappropriate for this case. However, Westerlund (2008) is perfectly suitable for this condition as it not only tolerates regressors integrated at mixed levels but also allows the estimation of datasets with CSD. This test applies the Durbin–Hausman principle and computes groups and panels statistics using common factors. The equations for panel and group statistics are as follows.

$$dh\_p = S_n(\delta+\delta)^2\sum_{i=1}^{n}\sum_{T=2}^{T}\hat{E}^2_{it-1} \tag{5}$$

$$dh\_g = \sum_{i=1}^{n}S_t(\delta+\delta)^2\sum_{t=2}^{T}\hat{E}^2_{it-1} \tag{6}$$

There are not many panel data methods that could simultaneously handle various panel data problems, including endogeneity, residual correlation, CSD, and fractional integration. In this context, this study used the renowned CuP-FM test of Bai et al. (2009), which addresses endogeneity, residual correlation, CSD, and fractional integration issues while estimating the long-run results. Thus, this method has become very popular in recent environmental economic literature for generating reliable estimates. Although this test is very reliable, the estimates of this study are also confirmed by using the CuP-BC test of Bai et al. (2009). The motivation behind adopting the CuP-BC test is that it also offers various advantages that are pretty similar to the benefits of the previously used CuP-FM test.

The use of the above tests will help us to acquire the coefficients for the long-run effects, which is the main goal of this paper. However, the causality method of Dumitrescu and Hurlin (2012) is also adopted for estimating the flow of causality between CO_2 and each regressor. This test is also appropriate for BRICS' cross-sectionally dependent panel. The flow of the estimation strategy can be seen in Fig. 1.

Results and discussion

Descriptive statistics in Table 1 show that CO_2 per capita (tonnes) reaches 13.95 in BRICS, and it has a minimum value of 0.74, mean value of 5.40, and standard deviation of 3.89. The country-specific trend in Fig. 2 further depicts that, CO_2 (in per capita form) is higher in Russia and South Africa compared to China which is number one in terms of total CO_2 emissions. Technology that depicts total patents has a mean value of 9566, and the maximum value is 1,542,002, while the minimum value is just 3140. Further detail in Fig. 3 depicts that China, Russia, and Brazil had more patents at the start of the period; however, technological innovation has boosted in India over the period of analysis, and India has surpassed Brazil and Russia in terms of total patents. Economic complexity has a standard deviation of 0.27 and a mean value of 0.33.

The analysis to know about the independence or dependence in Table 2 depicted that statistics in all three CSD tests are significant; hence, BRICS panel data possess dependence. This conclusion is vital for selecting tests

Fig. 1 Estimation strategy flow chart

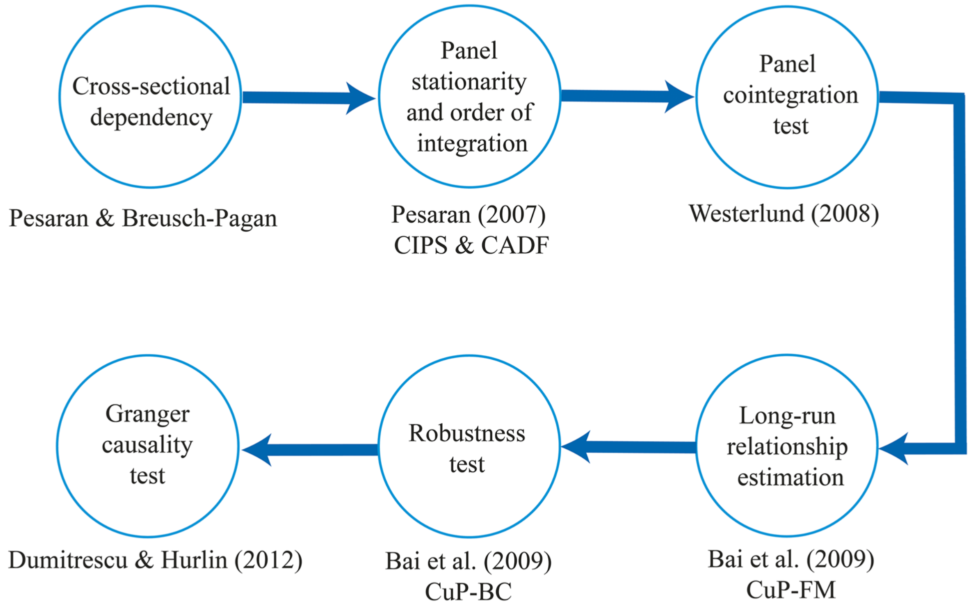
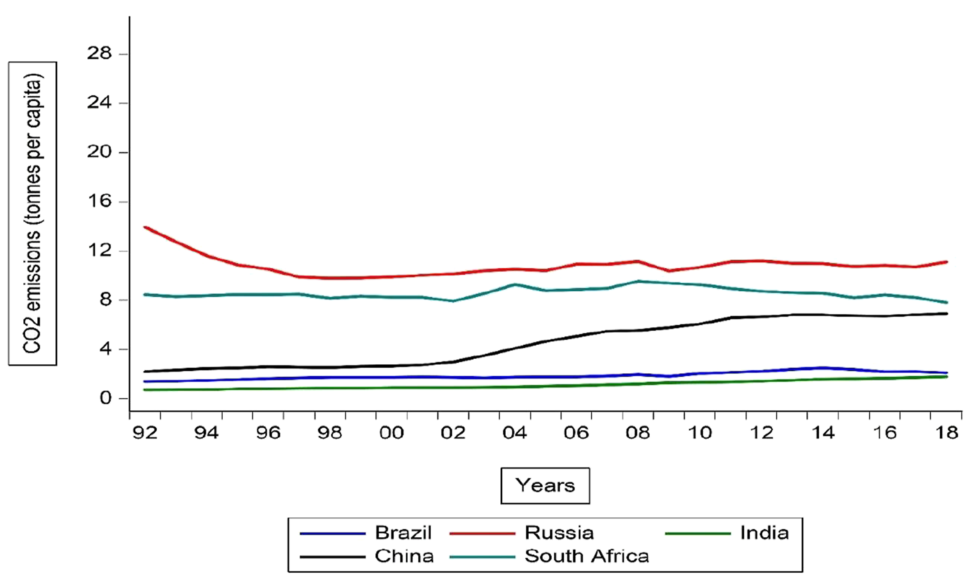


Table 1 Descriptive statistics

	CO_2	Y	ECC	TE	PD
Mean	5.406276	5368.955	0.332366	95,661.36	118.3855
Median	4.677525	5657.222	0.262064	24,774.00	39.46994
Maximum	13.95306	11,875.73	1.163790	1,542,002	454.9465
Minimum	0.745256	545.3995	−0.204966	3140.000	8.716096
Std. dev	3.893960	3213.777	0.273738	257,639.7	142.2808

Fig. 2 Trends of CO_2 emissions



for further analysis since some conventional tests ignore dependence in datasets during the estimation. Given the CSD in the dataset, it is important to choose some of the second-generation methods for useful results.

The application of Pesaran (2004) tests for unit root investigation in Table 3 illustrated that Y and TE are stationary. However, CO_2, ECC, and PD possess unit roots at 1(0). Therefore, the first difference of modeled variables

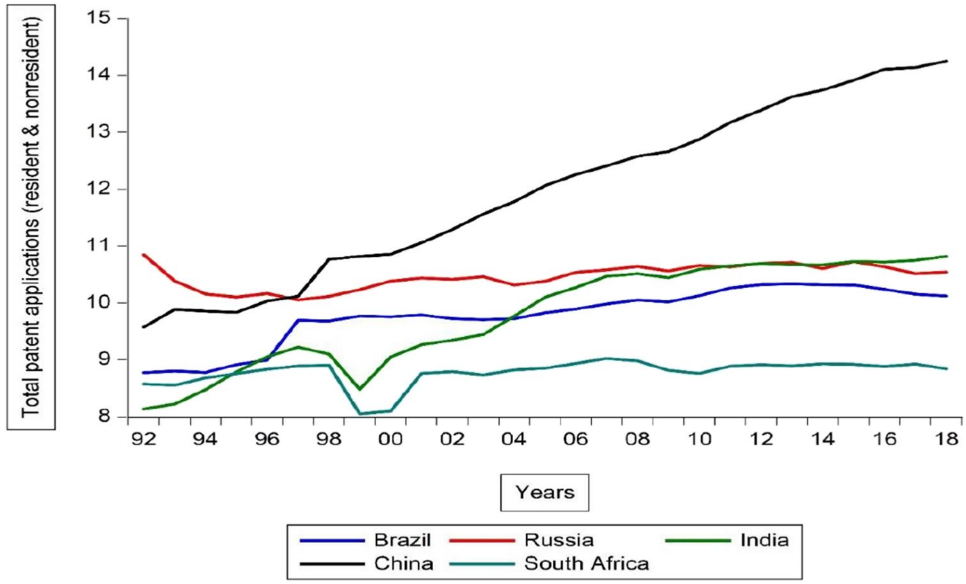


Fig. 3 Trends of technology

Table 2 Cross-sectional dependence (CSD)

Variables	Pesaran Scaled LM (PSL)	Pesaran CD	Breusch-Pagan LM (BPLM)
CO_2	14.444* [0.000]	5.114* [0.000]	74.598* [0.000
Y	51.662* [0.000]	15.517* [0.000]	241.039* [0.000]
ECC	20.920* [0.000]	4.808* [0.000]	103.560 [0.235]
TE	24.077* [0.000]	10.217* [0.000]	117.678* [0.000]
PD	51.046* [0.000]	4.255* [0.000]	238.288* [0.000]

*1% significance.

is taken, and the computation uncovered that CO_2, ECC, and PD became stationary in both tests (CADF and CIPS) at the first difference. Therefore, the overall results depict mixed stationary levels in the BRICS panel.

It is challenging to tackle this situation since only the response variable (CO_2) and regressors (ECC and PD) are stationary at the difference and many of the cointegration tests do not handle such fractional integration issues. Nevertheless, Westerlund's (2008) test is not only applicable to regressors stationary at 1(1) but also tolerates stationary regressors in panel models. The estimation of the model by using the Westerlund (2008) in Table 4 elucidated cointegration between ECC, ECC^2, Y, TE, PD, and CO_2 since the group statistics (dh_g) and panel statistics (dh_p) are statistically significant.

In Table 5, the estimates uncovered that increasing Y (economic growth) enhances CO_2, which infers that environmental quality reduces because of economic progress in BRICS. A 0.41% intensification in CO_2 is connected with a 1% upsurge in Y. This is because BRICS nations have achieved rapid progress over the last few decades. In these countries, economic growth has boosted for the period under analysis, and just in the last decade, these nations obtained 6.5% of the average growth rate. Currently, their overall contribution to global economic development is approximately 23% (Khan et al. 2020a). As

Table 3 Unit root tests

Variables	CADF		CIPS	
	Level	△	Level	△
CO_2	−2.064	−2.337***	−1.942	−3.420*
Y	−2.740**	−2.850*	−2.771*	−3.111*
ECC	−1.744	−3.933*	−2.006	−5.894*
TE	−2.564**	−2.960*	−3.414*	−4.429*
PD	−1.940	−3.288*	−2.063	−3.506*

, *, and * depict 5%, 10%, and 1% significance.

Table 4 Westerlund (2008) test

	Value	Prob
dh_g	−1.677**	0.047
dh_p	−1.521***	0.064

*** and ** denote 10% and 5% significance.

Table 5 Long-run estimation (CuP-FM)

Variables	Coefficients	T-stat
Y	0.414	9.291*
ECC	0.734	14.724*
ECCsq	− 0.281	− 15.236*
TE	− 0.105	− 4.060*
PD	0.328	9.034*

*1% significance.

BRICS are included in the developing group of nations, they overwhelmingly consume traditional fossil energy to support their economic growth. Their contribution to the world's energy consumption is approximately 40% (Qin and Ozturk 2021). Thus, the consumption of traditional energy sources for achieving economic growth degrades environmental quality in BRICS. This verdict is in consonance with Ahmad et al. (2022a) for BRICS, He et al. (2021) for 10 nations with a high energy transition, Wan et al. (2022) for India, Wang et al. (2020b) for APEC nations, Adebayo et al. (2022a) for BRICS, Wasif et al. (2021) for APEC nations, and Adebayo et al. (2021a) for South Korea.

Next, the coefficient ECC shows a positive connection with CO_2; however, the coefficient of ECCsq (ECC^2) is negatively linked with CO_2. This evidenced that currently, economic complexity in BRICS enhances environmental deterioration but after attaining a threshold level, the negative association between CO_2 and economic complexity will prevail. Thus, the association between ECC and CO_2 is like an inverted U-shaped curve. This fresh evidence supports our expectations of a non-linear impact of ECC on CO_2. This conclusion refutes the previously reported linear findings of Shahzad et al. (2021) for the USA, Neagu (2020) for most complex nations, Wan et al. (2022) for India, Boleti et al. (2021) for 88 countries, and Nathaniel (2021) for ASEAN.

However, the inverted U-shaped link aligns with the theoretical underpinnings of ECC since it is a challenge to get sufficient capabilities to master the production of less resource-intensive complex goods for developing nations like BRICS. Thus, with a rise in ECC, many energy-intensive goods are produced that intensify environmental issues (Doğan et al. 2019). Therefore, the positive coefficient of ECC is reasonable for BRICS that generate more than 40% CO_2 emissions. However, societies' preferences for saving the environment and energy-efficient green technologies are expected at a higher level of development when the ECC level significantly increases. Only at a very high level of ECC, nations can opt to dump dirty goods and enhance the share of complex and less resource-intensive goods (Can and Gozgor 2017). Hence, ECC^2 reduces CO_2 in the context of BRICS. The finding of his study deviates from many previous studies; however, it agrees with the results of Pata (2021) for the USA. Thus, BRICS nations can continue to expand their ECC levels to meet SDG 13 because a high ECC level will be beneficial in reducing CO_2 and thereby achieving the commitments regarding climate actions. This evidence supports the results of Balsalobre-Lorente et al. (2022) for PIIGS nations.

Technology has a significant coefficient in Table 5 which establishes that 0.10% mitigation in CO_2 is connected with a 1% rise in TE. Therefore, environmental quality in BRICS is improved due to technological innovation. This finding is in a similar vein to Shahbaz et al. (2020) for China, Zhao et al. (2021) for a global panel, Balsalobre et al. (2015) for OECD, Kihombo et al. (2021a, b) for WAME countries, Mensah et al. (2018) for OECD, and Khan et al. (2020b) for G7. However, it opposes the conclusion of Adebayo et al. (2021c) for China, Alvarez-Herranz et al. (2017) for OECD, and Sinha et al. (2020) for N 11, as both these studies established a positive connection between technology and environmental deterioration. Enhancing technology enables countries to uplift their energy efficiency because modern technology consumes less energy. Also, developing new technologies help to uplift green energy production enabling countries to gradually shift towards alternative energy (Kihombo et al. 2021a). BRICS nations are striving to boost their innovation. Interestingly, in some BRICS nations, innovation significantly increased over the selected period; for example, Chinese patents increased by 10,601% from 1992 to 2018. Also, enormous increases of 1361% and 747% were seen in total patents of India and Brazil, respectively. This shows that BRICS are in the process of upgrading their technologies with modern efficient technologies, and an increase in technology decreases their CO_2 emissions. This finding depicts that BRICS are on the right path to achieving SDG 9 as innovation is on an increase in this country group. Enhancing Technology will be useful in achieving sustainable industrialization which will pave the way towards sustainable development. Alongside this, upgrading reducing harmful effects of industrialization and the use of modern technology for green energy production will enable BRICS to achieve SDG13.

Finally, increasing PD by 1% enhances CO_2 by 0.328%, which illustrates that population density in BRICS is intensifying emissions levels in this country group. This makes sense because high population density in developing nations, where modern green infrastructures are fewer, enhances traffic congestion, resource consumption, and energy utilization in various sectors of the economy, which uplifts environmental pollution. This conclusion aligns with those of Rasool et al. (2019) for Pakistan, Kihombo et al. (2021b) for WAME nations, Lin et al. (2021) for China, and Nasreen et al. (2017) for South Asia. However, this result opposes the claims of Ahmed et al. (2019) for Malaysia and Ali et al. (2022) for India. After this, the long-run estimation is conducted using the CuP-BC test in Table 6. The results from this test elucidated the negative coefficients of ECCsq and TE. However, the coefficients of ECC, PD, and Y are positive. Hence, the reliability of long-run estimation is evident from the estimates of CuP-BC. The summary of findings is presented in Fig. 4.

Lastly, the analysis is conducted by using the DH causality test in Table 7. The results of this test indicated that the core variables, technology, and economic complexity, Granger, cause the CO_2 without any feedback. Thus, BRICS can design policies on these variables to influence CO_2. In addition, the feedback effect is noticed between Y and CO_2 and between PD and CO_2.

Table 6 Robustness of long-run estimation (CuP-BC test)

Variables	Coefficients	*T*-stat
Y	0.341	9.753*
ECC	0.370	11.726*
ECCsq	−0.283	−21.082*
TE	−0.072	−3.706*
PD	0.153	5.651*

*1% significance.

Table 7 Dumitrescu-Hurlin (DH) panel causality tests

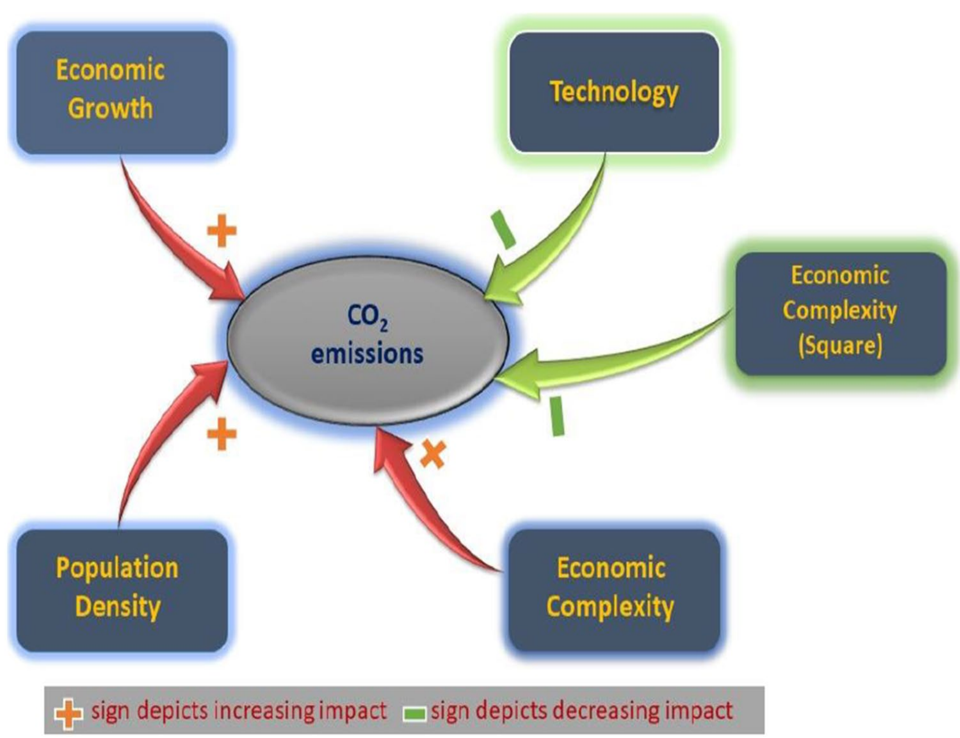
	W-stat	Prob	Decision
Y to CO_2	7.419*	0.000	
CO_2 to Y	9.441*	0.000	↔
ECC to CO_2	8.953*	0.000	
CO_2 to ECC	2.716	0.2961	→
TE to CO_2	4.732**	0.023	
CO_2 to TE	1.899	0.771	→
PD to CO_2	7.289*	0.000	
CO_2 to PD	19.079*	0.000	↔

** and * 5% and 1% significance

Conclusion and policies

This research probed the non-linear effects of economic complexity on CO_2, including technology, population density, and economic growth in the context of BRICS. To this end, Westerlund's (2008) test is adopted to assess the cointegration, and the CuP-FM test is applied to apprehend the long-run impacts. The results disclosed that CO_2, technology, economic complexity, and other selected variables are cointegrated. The long-run results uncovered an inverted U-shaped connection between ECC and CO_2. This suggests that a higher level of ECC benefits the environment compared to a low level of ECC which harms the environment. Technology is evidenced to mitigate environmental pollution

Fig. 4 Long-run results



in the context of BRICS. Also, the results revealed that CO_2 emissions upsurge on account of an increase in population density and economic growth. Furthermore, economic complexity and technology Granger cause CO_2.

These empirical estimates are vital to design strategies regarding SDGs 9 and 13 for accomplishing sustainable development and a green environment. The results depict that ECC beyond a certain level will lessen CO_2 and currently, ECC reduces the quality of the environment. Hence, it is critical to upsurge the ECC level in BRICS for improving environmental quality. However, to boost ECC, technological competencies are required. In this context, the findings also indicate that technological innovation lessens CO_2. Therefore, these results present a vital opportunity for BRICS to immediately focus on directing investments towards technology by designing various policies. In this context, the long-term strategy could be to boost the education level and academic research, which will eventually increase innovation and technology. Directing more funding for research in the academic institutes and increasing the collaboration between industries and universities will promote innovation in the industries. Offering lucrative tax benefits on technology-related projects can also boost domestic innovation and local technology. In this setting, upgrading the technology in the industrial sector will lead to sustainable industrialization, which will help BRICS to achieve SDG 9. On the other hand, the focus on innovation for producing complex goods can enable BRICS to gradually dump energy-intensive products from their export baskets. Thus, SDG 13 can also be realized since the reduction in energy usage will decrease CO_2.

To enhance the technology level regional cooperation can also be expanded by initiating some trade agreements with each other as some countries like China have better technologies compared to other BRICS nations. In this context, relaxed regulations and easy documentation for the import of advanced technologies, and beneficial investing opportunities for clean energy production can attract competencies and investments across this country group. This will reduce the use of conventional energy and stimulate energy transition, which in turn will minimize environmental pollution generated by the economic progress. To reduce the CO_2 emissions produced by economic growth, BRICS should focus on building modern efficient machinery for achieving a higher level of energy efficiency. Boosting energy efficiency can decrease the overwhelming usage of fossil fuels in industrial production. Alongside, raising the consumption of solar, wind, bioenergy, and other clean sources can limit the adverse environmental effects of economic growth. Finally, it is time for BRICS to plan their cities, initiate sustainable transportation, and improve public transportation to lessen the environmental repercussions of higher population density. Rail and bus-based transport can reduce energy usage and private vehicles, which in turn can bring down pollution levels. Also, strategies for increasing alternative fuels and clean vehicles can reduce environmental pollution generated by higher population density levels.

This study provides some new insights concerning economic complexity, technology, and CO_2 connection in BRICS; however, only a few determinants of CO_2 emissions are included during the empirical analysis. In this context, future works may add energy budgets, different sources of energy, human capital, and other important predictors of CO_2 for useful findings. Moreover, the research work can be replicated by adding some more variables in different regions and country groups for useful climate-related policies.

Author contribution GP: writing original manuscript; conceptualization; analysis FM: supervision; corrections; administration. ZA: writing original manuscript; helped in analysis; methodology. MA: writing review and editing; writing original manuscript. KK: writing review and editing.

Data availability Data set used in the study can be obtained by a reasonable request from the corresponding author.

Declarations

Ethics approval and consent to participate NA

Consent for publication NA

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