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Assessing the influence of green innovation and environmental policy stringency on CO_2 emissions in BRICS

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Abstract
This article examines the effect of environmental policy stringency and green innovation on CO_2 emissions in the BRICS nations, using annual data from 1990 to 2019 utilizing panel FMOLS and DOLS estimators and Method of Moments Quantile Regression (MMQR). To this end, we estimate an equation in which CO_2 emissions are explained by GDP, trade openness, nonrenewable and renewable energy consumption, the environmental stringency index, and green innovation, as measured by the number of patent applications for environmentally related inventions. FMOLS and DOLS results reveal that GDP, nonrenewable energy consumption, and trade openness have a positive effect on environmental pollution, whereas improvements in renewable energy consumption and environmental regulations lead to a drop in CO_2 emissions. However, green innovation does not have a significant effect on CO_2 emissions. MMQR estimates demonstrate that the GDP has a positive effect on CO_2 emissions across all quantiles, suggesting that a higher degree of economic growth is associated with higher emissions. Based on findings, empirical evidence suggests that BRICS countries should follow the policies encouraging the reduction of nonrenewable energy consumption in the region without harming the development of the economy. Besides, policymakers should promote renewable energy consumption and enhance investment in green innovation to achieve sustainable development and environmental quality.

Keywords Green innovation · Environmental policy stringency · CO_2 emissions · BRICS countries · MMQR

1 Introduction

The worldwide nature of the carbon emission reduction aim is underscored by the statistic provided by the Environmental Protection Agency (EPA, 2017), which indicates that carbon emissions account for 76% of global greenhouse gas emissions. However, despite extensive global initiatives, fossil fuels continue to maintain a significant presence in the energy mix. Alongside conventional strategies aimed at diminishing the reliance on fossil energy sources, recent emphasis has been placed on environmental policies that promote

Extended author information available on the last page of the article sustainable development and strive to surpass the environmental objectives that can be achieved through market mechanisms (OECD, 2016). These policies frequently necessitate more stringent environmental regulations, elevate the financial burden of polluting goods, and induce modifications in behavior among both producers and consumers. Namely, according to Khan et al., (2022), there is a contention that the inverse association between green innovation and consumer resistance towards these products diminishes when consumers possess a substantial degree of environmental knowledge. After the adoption of the Paris Agreement in 2015, there arose a pressing need for the engagement of both governmental entities and the private sector in the effective execution of environmental measures designed to facilitate the shift towards a more sustainable, low-carbon economy (Albulescu et al., 2022). According to Ahmed & Ahmed (2018), the Paris Agreement establishes explicit and legally enforceable objectives in order to address the necessity for more stringent environmental regulations in order to attain the specified aims. Nevertheless, conducting cross-country evaluations of the economic ramifications of environmental policies proves challenging owing to the dearth of comparable and dependable data. The Environmental Policy Strictness (EPSI) index, developed by the OECD, is widely recognized as a valuable indicator for assessing the effectiveness of environmental policies. This index specifically evaluates regulations pertaining to climate and air pollution (Afshan et al., 2022; Ahmed & Ahmed, 2018; Albulescu et al., 2022; Botta & Koźluk, 2014; Sezgin et al., 2021; Wolde-Rufael & Weldemeskel, 2020).

As the desired successes have not been achieved in the fight against climate change, the studies in this field to continue unabated. This situation was persistently expressed at the COP28 UN Climate Change Conference held in Dubai, United Arab Emirates in 2023. COP28 marked the outcome of the world's first 'global assessment' of efforts to combat climate change under the Paris Agreement. However, progress is very slow in all areas of climate action, from reducing greenhouse gas emissions to strengthening resilience to a changing climate, to providing financial and technological support to vulnerable nations. COP28 stressed out to accelerate the transition to renewable energy sources, especially wind and solar energy, and increasing concern about climate change.

Researchers interested in climate change and global warming often focus on identifying and mitigating key factors that contribute to environmental degradation. In this context, notwithstanding the perspectives positing that environmental deterioration is an inexorable consequence of economic expansion (IMF, 2020; Su et al., 2022; Apinran et al., 2022; Wan & Sheng, 2022) or an inherent outcome of the industrialization trajectory (OECD, 2020; Elfaki et al., 2022; Raihan et al., 2022), there exist viewpoints suggesting that the implementation of renewable energy sources in production activities could potentially mitigate environmental degradation (IPCC, 2012; IRENA, 2019). In this context, it is widely recognized that environmental degradation is not an inherent outcome of economic expansion or industrialization. It is emphasized that making appropriate energy source selections can effectively mitigate these issues. In essence, the primary concern lies in the utilization of fossil fuels within a nation's production activities (UNEP, 2023; Li et al., 2022a; Qiao et al., 2023).

Another crucial strategy for mitigating environmental pollution is green innovation, which encompasses both product and process innovation. Green innovation involves developing production processes and product designs that save energy, reduce pollution, and minimize waste, thereby reducing a firm's negative impact on the environment (Tang et al., 2018). Because green innovation integrates economic growth and environmental protection to support sustainable development, scientists and policymakers emphasize its importance as a solution-oriented tool for addressing environmental degradation (Koseoglu et al., 2022). In addition, Shen & Zhang (2023) propose that by encouraging green technology, intelligent manufacturing may improve environmental quality. However, while some researchers emphasize that green innovation is among the most effective strategies for reducing carbon emissions (Zhang et al., 2017; Xin et al., 2021; Ding et al., 2021; Jiang et al., 2022; Yunzhao, 2022; Albitar et al., 2022), others contend that green innovation alone is insufficient to limit global warming to below 1.5 °C (Bosetti et al., 2011; Töbelmann & Wendler, 2020).

Based on the provided information, the primary objective of this study is to examine the influence of environmental policy strictness on carbon emissions among the BRICS countries. There exist multiple justifications for selecting the BRICS countries as the sample. First, BRICS countries are selected as the focus of this study due to their substantial share of global CO_2 emissions. According to the International Energy Agency (IEA, 2021), the top five CO_2 emitters in 2020 were China, the United States, India, Russia, and Japan. China, with 10,540 $MtCO_2$, emitted nearly twice the amount of CO_2 as the second-largest emitter, the United States (4499 $MtCO_2$). India ranked third, emitting 2,619 $MtCO_2$, followed by Russia (1582 $MtCO_2$) and Japan (1139 $MtCO_2$). Additionally, Brazil and South Africa ranked among the top twenty CO_2-emitting countries, with emissions of 467 $MtCO_2$ and 335 $MtCO_2$, respectively. Second, the BRICS countries offer an interesting case for studying the impact of EPSI and green innovation. Namely, the number of environment-related patent applications, used as a proxy for green innovation, has consistently increased from 84,246.4 in 1999 to 185,924.7 in 2019 in OECD countries. China and India have experienced particularly significant growth in green innovation. China's environment-related patent applications rose from 601.5 in 1999 to 61,030.2 in 2019 and India's applications increased from 199.3 to 2974.8 during the same period (OECD, 2023). Although the total number of environment-related patent applications in the OECD is higher, the substantial increase observed in China and India indicates a growing focus on developing cleaner and more efficient technologies to address CO_2 emissions.

The present study aims to contribute to literature in several respects. First, although there are a bulk of studies in the literature analyzing the determinants of environmental degradation, a limited number of studies are conducted on the impact of environmental regulations. To our knowledge, this is the first study analyzing the effectiveness of environmental regulation policies and environmental technologies in the case of BRICS countries. Second, previous studies analyzing the effects of environmental regulations have widely utilized environmental taxes as a proxy variable. However, this paper employs the recently developed environmental stringency index (EPSI), allowing us to monitor the effectiveness of the implemented environmental policies. EPSI, developed by the OECD, is designed as a country-specific and internationally comparable measure of the stringency of environmental policy to evaluate the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. This index provides a multifaceted evaluation of regulations by considering the joint effects of factors such as the number of environmental regulations, the level of their implementation, and the availability of environmental information. Finally, in contrast with studies utilizing linear and point estimation of the factors affecting pollution, this article uses the rarely utilized Method of Moments Quantile Regression (MMQR) to examine the impact of environmental policy stringency and green innovation on CO_2 emissions. This methodology offers distinct advantages over alternatives as it takes into account the time variance and non-normality of the variables and the error term, thus providing a more robust estimate of the quantile effects of the variables on CO_2 emissions. Hence it allows us to assess the presence of significant variation in the relationship between the variables and environmental pollution at different emission levels.

The remainder of this article is structured as follows. The second section provides an overview of the existing literature on the causes of environmental pollution. The third section introduces the data and research methodology used in this study. The fourth section presents the empirical findings derived from the panel time series and MMQR estimates. Finally, the last section concludes the paper by providing policy implications based on the evidence obtained for the BRICS countries.

2 Literature review

Carbon emissions are often considered one of the main causes of global warming. Consequently, numerous scholars have conducted investigations to determine the factors influencing carbon emissions and to develop policy strategies to reduce them (Gelenbe & Caseau, 2015). This literature review focuses on studies examining the relationship between carbon emissions, economic growth, green innovation, and renewable energy.

2.1 Renewable energy consumption and environmental degradation

Climate change risks have prompted scholars to consider renewable energy consumption as a major element for lowering CO_2 emissions (Hao & Shao, 2021). However, the impact of renewable energy solutions on environmental quality may not always meet the expected standards due to socio-economic problems (Sharif et al., 2020). Consequently, extensive empirical studies have examined the effect of renewable energy consumption on carbon emissions in various countries and time periods.

Chiu & Chang (2009) used panel threshold regression models to analyze the connection between renewable energy consumption and carbon emissions for OECD countries from 1996 to 2005. Sulaiman et al., (2013) explored this relationship for Malaysia from 1980 to 2009, employing the Granger causality test. López-Menéndez & Moreno (2014) analyzed the European Union countries from 1996 to 2010 using fixed effects and random effects models. Bento & Moutinho (2016) focused on Italy from 1960 to 2011, applying the ARDL method. Boluk & Mert (2015) examined Turkey from 1961 to 2010 using ARDL methods. Al-Mulali & Ozturk (2016) analyzed 27 developed nations from 1990 to 2012 using the DOLS and discovered that an increase in the consumption of renewable energy reduces carbon emissions. Similarly, Dogan & Seker (2016) analyzed 23 developed countries from 1985 to 2011 using FMOLS and DOLS, and also observed a decrease in carbon emissions with an increase in renewable energy consumption. Using GMM and dynamic fixed effect estimators Adams & Acheampong (2019) concluded that consumption of renewable energy in 46 sub-Saharan African countries from 1980 to 2015 reduced carbon emissions. Rahman et al., (2022) confirmed these findings for 22 countries from 1990 to 2018 using the linear autoregressive distributed lag technique. Using FMOLS and DOLS, Balsalobre-Lorente et al., (2022) reported a negative relationship between renewable energy consumption and carbon emissions for Portugal, Ireland, Italy, Greece, and Spain from 1990 to 2019. Ehigiamusoe & Dogan (2022) analyzed 16 countries from 1990 to 2016 using FMOLS and found that an increase in renewable energy consumption reduced carbon emissions. This finding is found by Kirikkaleli et al., (2021) for Chile from 1990 to 2017, employing fully modified ordinary least squares and dynamic ordinary least squares methods; Adebayo et al., (2022b) used Morlet wavelet analysis to investigate the relationship between renewable energy consumption and carbon emissions for Portugal from 1980 to 2019. Some studies have also investigated the causal relationship between the consumption of renewable energy and carbon emissions. Using panel cointegration estimations, Sadorsky, (2009) discovered a causal association between carbon emissions and renewable energy usage for G7 nations between 1980 and 2005.

umerous studies have demonstrated a negative correlation between the consumption of renewable energy and carbon emissions. Using MMQR with fixed effects, Usman et al., (2021) discovered that the consumption of renewable energy decreased environmental degradation in G7 nations. Mehmood et al., (2023) analyzed G7 countries from 1990 to 2020 using CS-ARDL and a wavelet coherence approach and observed a negative relationship between renewable energy consumption and CO_2 emissions. Apergis et al., (2010) found a positive relationship between renewable energy consumption and carbon emissions in 19 developed and developing countries from 1984 to 2007. However, based on panel Granger causality tests, they concluded that renewable energy consumption does not reduce carbon emissions. Amri, (2017) also reported an insignificant impact of renewable energy consumption on Algeria's carbon emissions from 1980 to 2011 using ARDL methods. Similarly, Saidi & Omri (2020) examined 15 major renewable energy-consuming countries using FMOLS and VECM techniques and found no long-term relationship between renewable energy use and carbon emissions. Saidi & Mbarek (2016) obtained similar results for Canada, France, Japan, Netherlands, Spain, Sweden, Switzerland, the United Kingdom, and the United States from 1990 to 2013 using panel Granger causality tests. Using dynamic seemingly unrelated regression (DSUR), Kongbuamai et al., (2021) discovered that BRICS countries' consumption of renewable energy decreased environmental degradation from 1995 to 2016. The results indicate that the relationship between renewable energy consumption and carbon emissions varies depending on the methodologies employed, the countries sampled, and the time periods examined.

2.2 EPSI and environmental degradation

Numerous studies have examined the relationship between EPSI and CO_2 emissions in different countries. Using Panel Pooled Mean Group Autoregressive Distributive Lag (PMG-ARDL) estimation, Wolde-Rufael & Weldemeskel (2020) identified an inverted U-shaped relationship between EPSI and carbon emissions for Brazil, Russia, India, Indonesia, China, Turkey, and South Africa between 1993 and 2014. Afshan et al., (2022) utilized MMQR to demonstrate that environmental policy index scores were negatively correlated with environmental degradation for OECD countries between 1990 and 2017.Using linear and non-linear panel ARDL models, Yirong, (2022) examined the effect of EPSI on CO_2 emissions for the top five carbon emitting nations (China, United States, India, Russia, and Japan) from 1990 to 2019. According to the results of both models, an increase in EPSI reduces CO_2 emissions over time. Albulescu et al., (2022) analyzed 32 OECD countries from 1990 to 2015 and discovered that EPSI reduces CO_2 emissions, with asymmetric effects.

Employing the nonlinear autoregressive distributed lag (NARDL) model, Assamoi & Wang (2023) demonstrated that a positive change in EPSI leads to decreases in environmental degradation and vice versa in China and the US. Wang et al., (2020) used the System Generalized Moments methodology to show a negative effect of EPSI on CO_2, NO_x, and SO_x emissions but a weak effect on PM2.5 emissions in 23 OECD countries from 1990 to 2015. Using the NARDL methodology, Chen et al., (2022) found that a positive shock in EPSI reduced CO_2 emissions and GHG emissions, whereas a negative shock increased N2O, PM2.5, and CO_2 emissions in China from 1993 to 2019. Li et al., (2022b) used the CS-ARDL model to determine that EPSI leads to a decline in environmental degradation in OECD economies from 2001 to 2018. The following studies also reported similar results: De Angelis et al., (2019) for 32 countries from 1992 to 2012 using Ordinary Least Squares; Kongbuamai et al., (2021) for BRICS countries from 1995 to 2016 using the novel Dynamic Seemingly Unrelated Cointegrating Regressions (DSUR) methodology; Fatima et al., (2023) for 36 OECD countries from 1990 to 2020 utilizing panel ARDL based on the PMG methodology; Udeagha & Ngepah (2023) for BRICS countries from 1960 to 2020 using CS-ARDL; and Umar & Sufi (2023) for OECD countries from 1990 to 2019 employing MMQR analysis,

2.3 Green innovation and environmental degradation

Numerous researchers have explored the relationship between innovation and CO_2 emissions using a range of measures and methodologies. Using the cross-sectional augmented autoregressive distributed lags method (CS-ARDL), Shao et al., (2021) found that green innovation had an insignificant impact on CO_2 emissions in the short run but led to a decrease in CO_2 emissions in the long run for N-11 countries from 1980 to 2018. Ahmad et al., (2020) used simultaneous equation modeling (SEMs) to show that innovations contributed to CO_2 emissions in 24 OECD countries during the period 1993–2014. The same result was found for 26 OECD countries using the fully modified ordinary least squares (FMOLS) methodology by Ahmad et al., (2021). Iqbal et al., (2021) found that environment-related technological innovation decreased CO_2 emissions for 37 OECD countries from 1970 to 2019. However, this contradicts a number of other studies reporting no effect: Usman & Hammar (2021) for APEC countries from 1990 to 2017, employing the augmented mean group (AMG) common correlated effects mean group (CCEMG) estimators; Usman et al., (2021) for G-7 countries using MMQR with fixed-effects; Fatima et al., (2023) for 36 OECD countries from 1990 to 2020 using panel ARDL based on the PMG methodology; Udeagha & Ngepah (2023) for BRICS countries from 1960 to 2020 utilizing CS-ARDL; and Umar & Safi (2023) for OECD countries from 1990 to 2019 employing MMQR analysis.

From their study of Pakistan based on quarterly data from 1990 to 2010 using ARDL methodology, Abbasi et al., (2022) found that innovation reduced CO_2 emissions, although the effect was minimal. This result aligns with Ning et al., (2023) for Pakistan during for 1980–2019 utilizing ARDL model and frequency domain causality. Using Morlet wavelet analysis, Adebayo et al., (2022b) showed that technological innovation contributed to CO_2 emissions in Portugal from 1980 to 2019. This finding is supported by a number of other studies: Obobisa et al., (2022) for 25 African countries from 2000 to 2018 employing AMG and CCEMG approaches; Usman & Radulescu (2022) for nine top nuclear energy-producing countries from 1990 to 2019 using AMG and CCEMG estimators; and for South Africa Udeagha & Ngepah (2022) using the quantile autoregressive distributed lag (QARDL) model.

In summary, the literature on the relationship between green innovation and environmental degradation reveals mixed findings. While some studies suggest that green innovation reduces CO_2 emissions, others find insignificant or even positive effects. These variations in findings can be attributed to the different measures of innovation and methodologies used, and the specific context of the countries studied.

2.4 Literature gap

The literature reviewed emphasizes the significance of comprehending the factors influencing carbon emissions and environmental degradation. It has been noted that the correlation between energy consumption and CO_2 levels has been extensively researched, with results consistently implying a predominantly positive relationship. This suggests that efforts aimed at decreasing carbon emissions should prioritize reducing energy consumption. Furthermore, it has been noted that the influence of renewable energy consumption on carbon emissions differs among various studies. Some studies report a negative correlation, while others find no significant or positive impacts. In recent studies, there has been a focus on the impacts of environmental policy regulations and green innovations as key elements in maintaining the global temperature increase at 2.1 °C above pre-industrial levels, aligning with the 2050 net zero emission goal established by the Paris Agreement (IEA, 2023). Therefore, the primary objective of this article is to fill this gap in the literature by analyzing the determiners of CO_2 for the BRICS case in a nonlinear framework.

3 Data and research methodology

3.1 Data and model

This paper utilizes panel data for the BRICS countries, i.e., Brazil, Russia, India, China, and South Africa, based on annual data covering the period from 1990 to 2019. For this purpose, CO_2 emissions are assumed to be a function of the following variables:

$$CO2_{it} = f(GDP_{it}, NREC_{it}, REC_{it}, EPSI_{it}, GI_{it}TRADE_{it}) \tag{1}$$

where GDP_{it} represents GDP per capita in constant 2015 US dollars. NEC_{it} and REC_{it} represent nonrenewable and renewable energy consumption in kilotons of oil equivalent, respectively. The EPSI index, $EPSI_{it}$, is defined as a country-specific measure of the stringency of environmental policy, while the green innovation GI_{it} variable is proxied by the number of patent applications related to environmental technologies. $TRADE_{it}$ represents trade openness as a percentage of GDP, as one of the important control variables affecting CO_2 emissions. Data for EPS_{it} and GI_{it} are sourced from the OECD database while the remaining variables are sourced from the International Energy Agency and DataStream database (Refinitiv Eikon DataStream, 2021). The variables are used in their natural logarithmic form to interpret the parameter estimates in terms of elasticities.

As explained previously, in contrast with methodologies providing single-point estimation of the parameter, MMQR is able to provide robust parameter estimates even in the case of non-normality, asymmetry, and heteroscedasticity in the data. Hence, to justify the use of this estimator, the descriptive statistics of the study variables are presented in Table 1. It is noteworthy that the skewness of all the variables is different from zero, indicating the presence of asymmetric distributions. This suggests the possible non-linear associations between the variables and CO_2 might not be addressed by linear estimation methodologies. The kurtosis values of the variables further support the non-normality of the variables in the model by deviating from the expected value of three for a normal distribution. The

Table 1 Descriptive statistics of the variables

	$lnCO_{2it}$	$lnGDP_{it}$	$lnNREC_{it}$	$lnREC_{it}$	$lnEPSI_{it}$	$lnGI_{it}$	$lnTRADE_{it}$
Mean	1.287561	8.264089	12.33870	10.23387	0.525071	4.363167	3.628269
Maximum	2.682491	9.225770	14.50385	12.23240	1.372308	8.684425	4.705713
Minimum	−0.434704	6.270796	10.58611	7.562757	0.000000	1.091923	2.718370
Std. Dev	0.916940	0.863906	1.066635	1.651111	0.355830	1.571280	0.402600
Skewness	−0.184512	−0.952355	0.139766	−0.320004	0.677720	0.619991	−0.445364
Kurtosis	1.634781	2.535017	2.122206	1.488414	2.778798	3.441865	2.407852
Jarque–Bera	12.50000	24.02582	5.304124	16.84063	11.78843	10.83001	7.150232
Probability	0.001930	0.000006	0.070506	0.000220	0.002755	0.004449	0.028012

Jarque–Bera tests for normality and their probabilities reported at the end of Table 1 also corroborate the nonnormality of the variables by rejecting the null hypothesis of normal distribution as the probabilities are below 5% for all the variables, apart from the natural log of total energy consumption. In summary, the non-normal distribution of these variables further corroborates the use of MMQR, as it is a robust method that is able to deal with non-normality and heteroscedasticity effectively.

3.2 Method of moments quantile regression

Considering the documented nonnormality of the variables in the analysis, this section provides a brief overview of the MMQR methodology for robust estimation of the determinants of CO_2 emissions. The equation is first expressed in the panel fixed-effect form as follows:

$$lnCO_{2it} = \beta_0 + \beta_1 lnGDP_{it} + \beta_2 lnNREC_{it} + \beta_3 lnREC_{it} + \beta_4 lnEPS_{it} + \beta_5 lnGI_{it} + \beta_6 lnTRADE_{it} + \varepsilon_{it} \quad (2)$$

Then, following Machado & Silva (2019) the above equation converted into the following location-scale model where the parameters are estimated based on the conditional quantiles of the dependent variable, i.e. $Q_Y(\tau|X)$,:

$$Y_{it} = \alpha_i + X'_{it}\beta + (\delta_i + Z'_{it}\gamma)U_{it} \quad (3)$$

where Y_{it} is the vector dependent variable, i.e. the natural log of CO_2 emissions. X'_{it} is the matrix of explanatory variables defined as $X'_{it} = [lnGDP_{it} lnNREC_{it} lnREC_{it} lnEPS_{it} lnGI_{it} lnTRADE_{it}]'$.

The parameters to be estimated for analysis are $\left(\alpha, \beta', \delta, \gamma'\right)'$, whereby $\left(\alpha_i, \delta_i\right)$, $i = 1, 2, \ldots, n$ shows the individuals fixed effect while Z_{it} is the k-vector of known differentiable transformations of the X_{it} with element I, $Z_l = Z_l\left(X_{it}\right), l = 1, 2, \ldots, k$ satisfying the following probability condition $P\left\{\delta_i + Z'_{it}\gamma > 0\right\} = 1$. U_{it} is an unobserved random variable independent of X_{it} and it is normalized to satisfy the following moment conditions:

$$E(U_{it}) = 0, E(\left|U_{it}\right|) = 1 \quad (4)$$

Based on these conditions and the exogeneity of the explanatory variables, the parameters to be estimated, α_i, $\beta', \delta_i, and\ \gamma'$, $q(\tau)'$ are obtained based on the first moment

Table 2 Bias-adjusted LM test of error cross-section independence

Test	Statistic	*p* value
LM	16.89	(0.0768)
CD_{LM}	−0.0615	(0.9510)
LM_{adj}	3.121	(0.0018)

Table 3 Panel unit root tests

	IPS		LLC	
	level	First difference	level	First difference
$lnCO_{2it}$	−0.025	−3.037**	−0.690	−2.572***
$lnGDP_{it}$	1.421	−3.619***	−0.253	−2.437***
$lnNREC_{it}$	0.793	−4.154***	−0.190	−2.902***
$lnREC_{it}$	2.050	−3.120***	1.067	−1.922**
$lnEPSI_{t}$	0.549	−5.757***	1.689	−6.656***
$lnGI_{it}$	0.054	11.482***	−1.054	−8.919***
$lnTrade_{it}$	0.937	−2.722***	1.793	−12.484***

***and ** denote statistical significance at 1% and 5% level, respectively

conditions defined in Machado & Silva (2019). Therefore, the final form of the conditional quantile representation of the model is defined as below:

$$Q_Y\left(\tau|X_{it}\right) = \left(\alpha_i + \delta_i q(\tau)\right) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \tag{5}$$

The scalar coefficient $i(\tau) \equiv \left(\alpha_i + \delta_i q(\tau)\right)$ in parenthesis represents the quantile-τ fixed effect for individual i, or the distributional effect at τ. The MMQR parameter estimation relies on Hansen's (1982) one-step GMM estimator. Thus, it is useful for the models in which endogeneity challenges the reliability of parameter estimates. Furthermore, due to the conditional quantile estimation of the parameters, it is less affected by distributional assumptions, which could make it more resistant to deviations from the normal distribution assumed by OLS.[1]

4 Empirical results

4.1 The results from panel time series

To investigate the impact of the independent variables on CO_2 emissions, a panel time series analysis was conducted. First, the presence of cross-sectional dependence between variables was examined using the CD test proposed by Pesaran, (2004). The results indicated no significant cross-sectional dependence among the variables (see Table 2).

[1] Readers may refer to Machado and Silva (2019) for more details on the estimation steps of the MMQR model.

Table 4 Panel cointegration tests

	Statistic	p value
a. Pedroni		
Modified Phillips-Perron t	1.4534	0.0731
Phillips-Perron t	−2.3002	0.0107
Augmented Dickey-Fuller t	−2.1827	0.0145
b. Kao		
Modified Dickey-Fuller t	−5.4666	0.0000
Dickey-Fuller t	−3.9576	0.0000
Augmented Dickey-Fuller t	−1.7219	0.0425
Unadjusted modified Dickey-Fuller	−6.4351	0.0000
Unadjusted Dickey-Fuller t	−4.1417	0.0000

Table 5 Long-run parameter estimates

Dependent variable: $lnCO_{2it}$	FMOLS	DOLS
$lnGDP_{it}$	0.28***	0.49***
$lnGI_{it}$	0.01	−0.02
$lnEPSI_{it}$	−0.04***	−0.04***
$lnNREC_{it}$	0.69***	0.42***
$lnREC_{it}$	−0.39***	−0.16***
$lnTRADE_{it}$	0.02***	0.02***

***, **, and * represent statistical significance at 1%, 5%, and 10% level respectively

Therefore, panel IPS (Im et al., 2003) and LLC (Levin et al., 2002) unit root tests were conducted to assess the stationarity of the variables (see Table 3).[2] The IPS and LLC unit root test statistics yielded identical results regarding the integration properties of the variables. They indicate that the variables have a unit root at the level; consequently, the unit root null hypothesis could not be rejected. However, after taking the first difference, all variables become stationary, indicating that they are integrated of order one.

After confirming that the variables had the same degree of integration, the presence of a long-run relationship between the variables was investigated. Based on the conclusion of the cross-sectional dependence tests, we employ Pedroni, (1999) and Kao, (1999) cointegration tests. (see Table 4). In the Pedroni test, except for the Modified Phillps-Perron t statistics, individual statistics seem to be statistically significant at 5% level of significance. This suggests that there might be evidence of cointegration. In the Kao, (1999) test, several of the statistics, particularly the modified Dickey-Fuller t statistic and the unadjusted modified Dickey-Fuller statistic, have very low p values, less than 1%, leading to the rejection of null of no long-run relationship. This provides strong evidence in favor of cointegration using the Kao test. Overall, the results seem to suggest the presence of a cointegrating relationship among the variables for both tests.

[2] Individual effects and a deterministic time trend are included in the panel unit root test specifications. The Akaike information criterion (AIC) is employed to determine lag length, with a maximum lag of four. The Bartlett kernel is used for spectral estimation, and the bandwidth is chosen by Newey and West's automatic lag selection.

Based on the evidence on the long-run relationship, the long-run parameters of the CO_2 equation were estimated using both the FMOLS and DOLS estimators, as shown in Table 5. The findings show that, with the exception of green innovation, the parameters of all variables are found to be statistically significant. The FMOLS and DOLS estimators indicate that an increase in GDP has a positive and significant effect on carbon emissions. For example, a 1% increase in GDP per capita corresponds to a 0.28% and 0.49% rise in CO_2 emissions, respectively. This result is supported by Meng et al., (2022) for BRICST countries and Li et al., (2023) for BRICS countries. However, the coefficient of green innovation is statistically insignificant. Hafeez et al., (2022) and Kuang et al., (2022) reached similar results in the short run for highly polluted Asian economies and China, respectively. The parameter of EPSI is negative and significant for both FMOLS and DOLS, which supports the importance of increasing environmental regulations to reduce CO_2 emissions in BRICS countries. A 1% increase in EPSI leads to a decrease in CO_2 emissions by 0.04% for both FMOLS and DOLS results. This finding is supported the study of Dai & Du (2023). Nonrenewable energy consumption has a positive and significant effect on CO_2 emissions. Our results showed that a 1% increase in nonrenewable energy consumption increased CO_2 emission by 0. 0.69% and 0.42% for both FMOLS and DOLS estimators. This finding is confirmed the results of Wolde-Rufael & Weldemeskel (2020) for BRIICTS countries. The positive and significant impact of trade openness on environmental degradation is reported. According to both estimators, a 1% increase in trade results in a 0.02% increase in CO_2 emissions. This result is aligned with the study of Naqvi et al., (2020) four different income groups, Chen et al., (2021) and Chhabra et al., (2022) for middle income countries, Udeagha & Ngepah (2023) for BRICS countries.

4.2 MMQR estimation results

The above panel time series results are derived from long-run OLS-based estimators. However, due to the non-normality of the data, point estimation of the coefficients may produce misleading results. As previously mentioned, the MMQR remains unaffected by the nonnormal distributional characteristics of the variables due to its design as a regression method that utilizes a set of explanatory variables to estimate the conditional quantiles of a response variable. The results of the MMQR estimation is displayed in Table 6 for various quantiles of the dependent variable CO_2 emissions. The threshold values for classifying the distribution of CO_2 emissions into five distinct groups are denoted by quantiles (0.1, 0.25, 0.5, 0.75, and 0.9). The parameter estimates derived from the MMQR at each quantile are also plotted in Fig. 1.

Similar to FMOLS and DOLS parameter estimates, an increase in GDP ($lnGDP_{it}$) has a positive and statistically significant effect on CO_2 emissions at all quantiles. However, the magnitude of the effect increases with quantile for example at the 0.1 quantile, a 1% increase in GDP leads to a 0.279% increase in CO_2 emissions. However, at the 0.9 quantile, the impact of 1% increase in GDP lead to a 0.494% increase in CO_2 emissions. This finding suggests that degrading effects of increase in GDP is more pronounced for higher emitters. This finding is confirmed by number of studies, e.g. Xie & Jamaani (2022) for G-7 countries, Afshan et al., (2022) and Xie et al., (2023) for OECD countries.

Regarding the impacts of green innovation, MMQR produces significant parameter estimates at certain quantiles, unlike the long-run estimates presented in the previous section. The results of MMQR indicate that green innovation ($lnGI_{it}$) has a negative impact on CO_2 emissions. Nevertheless, the impact is only statistically significant at higher quantiles,

Table 6 MMQR parameter estimates by quantile

Dependent variable: $lnCO_{2it}$

			Quantiles				
Regressors	Location	Scale	0.1	0.25	0.5	0.75	0.9
$lnGDP_{it}$	0.378***	0.067**	0.279**	0.314***	0.365***	0.436***	0.494***
	(0.044)	(0.026)	(0.045)	(0.041)	(0.042)	(0.058)	(0.074)
$lnGI_{it}$	−0.269*	−0.115	−0.099	−0.159	−0.246*	−0.37*	−0.469*
	(0.145)	(0.087)	(0.150)	(0.135)	(0.139)	(0.190)	(0.247)
$lnEPSI_{it}$	−0.067**	0.032**	−0.113***	−0.097***	−0.073***	−0.039	−0.012
	(0.027)	(0.016)	(0.027)	(0.025)	(0.026)	(0.035)	(0.045)
$lnNREC_{it}$	0.249***	−0.01	0.264***	0.259***	0.251***	0.24***	0.231***
	(0.03)	(0.018)	(0.031)	(0.028)	(0.029)	(0.039)	(0.051)
$lnREC_{it}$	−0.233***	0.034**	−0.283***	−0.265***	−0.239***	−0.203***	−0.173***
	(0.028)	(0.017)	(0.029)	(0.027)	(0.027)	(0.038)	(0.048)
$lnTRADE_{it}$	1.033***	0.073	0.926***	0.964***	1.019***	1.096***	1.159***
	(0.118)	(0.071)	(0.122)	(0.110)	(0.113)	(0.154)	(0.201)

***, **, and * represent statistical significance at 1%, 5%, and 10% level respectively. Standard errors of the coefficients are presented in parentheses

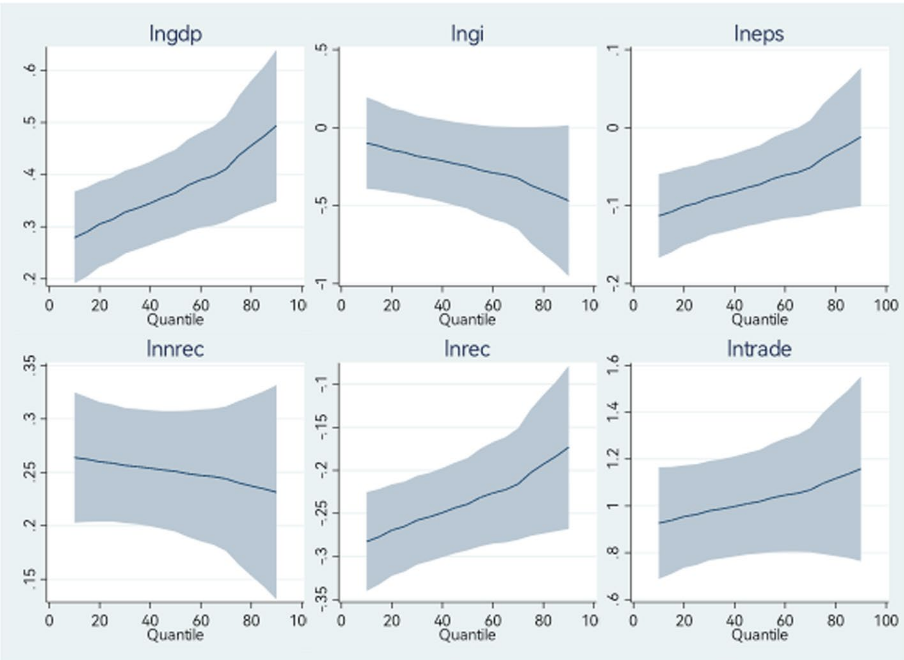

Fig. 1 MMQR parameter plots

indicating that green innovation has a more pronounced effect on emissions for high emitters. At the 0.1 quantile, a 1% rise in green innovation leads to a −0.099% reduction in CO_2 emissions, but the adverse impact is not significant until the 0.25 quantile. At the 0.9 quantile, there is a 0.469% decrease in CO_2 emissions following a 1% rise in environmental policy stringency. The rising negative impacts of green innovation also indicate that investments in green innovation may have a greater impact on countries with higher emission levels. This evidence is aligned with Sun et al. (2022) for the ten most polluting countries, Umar & Safi (2023) for OECD countries, Ramzan et al., (2023) for the world's ten greenest countries, and Lisha et al., (2023) for BRICS.

Trade openness $\left(lnTRADE_{it}\right)$ also has a positive and statistically significant effect on CO_2 emissions at all quantiles, indicating that more open economies tend to emit more CO_2. It is worth mentioning that MMQR estimates show that among the other variables, trade openness turns out to be the most impacted variable on CO_2 emissions. For instance, at the 0.1 quantile, a 1% increase in trade openness leads to a 0.926% increase in CO_2 emissions. At the 0.9 quantile, the impact increased to 1.096%.

The coefficient estimates for environmental policy stringency ($lnEPSI_{it}$) are found to be negative in line with the results of FMOLS and DOLS. However, they are statistically significant at lower quantiles (0.1, 0.25, and 0.5) but not significant at higher quantiles (0.75 and 0.9). The negative and statistically significant relationship between environmental policy stringency and CO_2 emissions at lower quantiles implies that the countries implementing more stringent environmental policies may effectively reduce emissions, particularly at lower emission levels. These results are aligned with Afshan et al., (2022) and Xie et al., (2023) conducted on OECD countries, Li et al., (2023) for BRICS countries.

Nonrenewable energy consumption ($lnNREC_{it}$) has a positive and significant effect on CO_2 emissions at all quantiles, indicating that higher nonrenewable energy consumption leads to higher emissions. The effect magnitude is relatively consistent across all quantiles, suggesting that the impact of energy consumption on emissions is relatively stable across different levels of emissions. This finding is in line with the results of Li et al., (2023) for BRICS countries, Adebayo et al., (2022a) for the most economically complex economies, and Adebayo et al., (2022c) for the MINT countries.

Finally, MMQR parameter estimates indicate that renewable energy consumption ($lnREC_{it}$) has a negative and statistically significant effect on CO_2 emissions at all quantiles, suggesting that an increase in the renewable energy usage leads to lower CO_2 emissions. These findings are corroborated by Anwar et al., (2021) for ASEAN countries, Xie & Jamaani (2022) for G-7 countries, Sun et al. (2022) for ten most polluting countries, and Li et al., (2023) for BRICS countries. The magnitude of the effect has a declining pattern with the increase in quantiles, suggesting that the impact of renewable energy consumption on emissions is more pronounced for low emitters.

Overall, the estimation results suggest that economic growth and trade openness are the most significant drivers of CO_2 emissions, while EPSI, green innovation, and renewable energy consumption can help to mitigate environmental degradation.

5 Conclusions and policy implications

This study analyzed the impact of EPSI and green innovation on CO_2 emissions in the BRICS countries. The study was motivated by the fact that the BRICS countries, as a group, have become both major emitters of greenhouse gases and the largest consumers of fossil fuels. The study therefore investigated whether green innovation and strict environmental policies can help these countries reduce carbon emissions and mitigate climate change.

The analysis was conducted with panel data from 1990 to 2019 using MMQR estimation methodology. The MMQR estimation method offers distinct advantages over alternative estimators because it provides a more robust estimation of the coefficients' quantile effects. This was crucial in the present study for understanding the impact of EPSI and green innovation on CO_2 emissions across different levels of emissions.

The empirical findings provided two main important insights into the relationship between EPSI, green innovation, and CO_2 emissions in the BRICS countries. First, the MMQR estimation results indicated that EPSI has a negative and statistically significant effect on CO_2 emissions in the BRICS countries. This implies that stricter environmental policies are associated with lower carbon emissions. Second, green innovation has a negative and statistically significant effect on CO_2 emissions, indicating that increased green innovation efforts are associated with reduced carbon emissions.

The study's findings yield several significant policy recommendations. In light of the inconclusive impact of EPSI on emissions, particularly in low-emission BRICS nations, it is recommended that environmental policies be formulated to suit the unique circumstances of each low-emission country. (i) When establishing regulatory standards, it is imperative to consider several factors, including but not limited to the economic structure, energy resources, industrial mix, and geographical aspects. (ii) It is recommended to adopt a progressive enforcement strategy, wherein environmental rules are initially set at a moderate level and subsequently strengthened in a gradual manner. This enables various industries and relevant parties to adjust and generate novel ideas in order to address changing requirements. (iii) It is imperative to build effective and resilient enforcement systems in order to guarantee adherence to environmental legislation. The implementation of monitoring mechanisms, sanctions for non-compliance, and regular audits is crucial for ensuring and upholding accountability. (iv) The integration of legal measures aimed at promoting compliance should be complemented by the implementation of positive incentives. Industries and individuals who surpass compulsory environmental criteria should be provided with rewards, recognition, and advantages. (v) Investments ought to be allocated towards enhancing the technical and institutional capabilities of regulatory bodies with the aim of efficiently executing and overseeing environmental legislation. The provision of training and resources has the potential to enhance the capacity of institutions to effectively implement regulatory measures.

The analysis conducted in this paper has some limitations that need to be addressed by further studies. First, it is important to note that our estimation results are limited to the BRICS. Therefore, a similar analysis may be conducted for the other economic blocs, such as APEC or EU countries. Second, our analysis is only focused on the determinants of CO_2 emissions, representing only one dimension of air pollution. Hence, the analysis conducted in the present paper can be extended with the employment of alternative environmental indicators using other air quality indicators, such as SO_2 or $PM1_0$ suspended particulate matter. Furthermore, based on the aim of the study, the ecological footprint might be used to account for not only pollution in the air but also pollution in the soil and water.

Appendix

See Figs. 2 and 3.

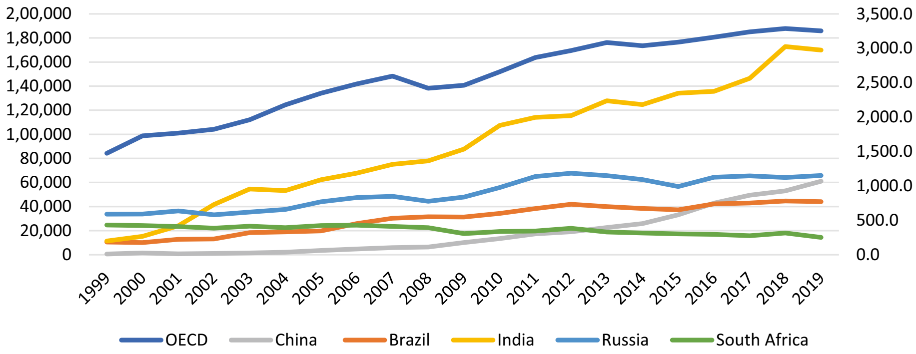

Fig. 2 Number of environment-related patent applications (green innovation) in BRICS countries and OECD

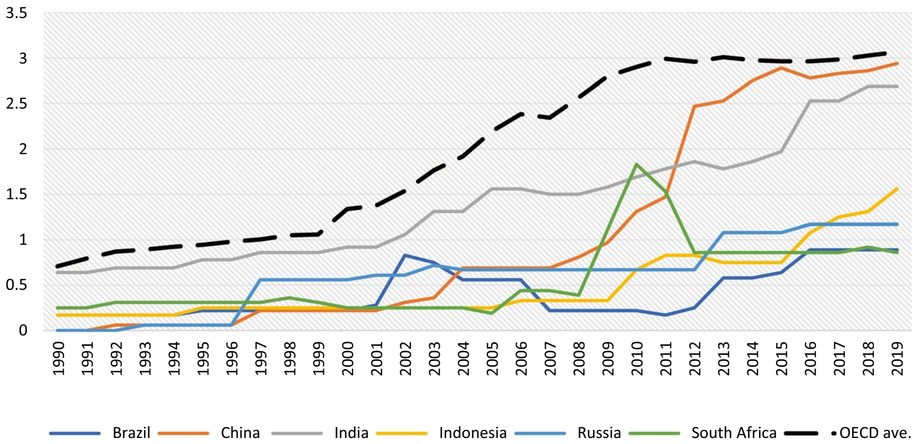

Fig. 3 EPSI Index Scores for BRICS countries and OECD

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Declarations

Conflict of interest None, no conflict of interest.

Ethical approval This article does not contain any studies with human participants. Performed by any of the authors.

Consent for publication Our study does not contain individual person's data.

Consent to participate No human or animal subjects were used in our study, and no questionnaire was conducted.

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