Heterogeneous impacts of renewable energy and environmental patents on CO_2 emission - evidence from the BRIICS

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Abstract: The study explores the impacts of renewable energy, environmental patents, economic growth and other variables on the CO_2 emission per capita from 2000 to 2013 for the BRIICS countries. Using both the panel OLS methods and panel quantile regression method, we find that the effects of the determinant variables are heterogeneous across quantiles. Specifically, renewable energy supply reduces CO_2 emissions per capita, with the strongest effect at the 95th quantile. Development of environmental patents accelerates carbon emissions per capita, but only significantly affects the CO_2 emissions per capita at the upper tail of the conditional distribution. GDP per capita enhances CO_2 emissions per capita, with the most substantial effect in the 5th quantile. Exports increase carbon emissions per capita with an asymmetric inverted U-sharped impact. Foreign direct investment reduces carbon emissions per capita, but only significantly influences the carbon emissions per capita at the medium and upper of the conditional distribution. Domestic credit to private sectors raises carbon emissions per capita with gradually decreasing impacts along all quantiles. We propose several policy recommendations based on the results.

Keywords: BRIICS; CO_2 emissions; environmental patent; panel quantile regression; renewable energy

1. Introduction

Brazil, Russia Federation, India, Indonesia, China and South Africa, six of very promising emerging national economies, constitute the BRIICS[1]. The BRIICS not only have significant impacts on global affairs due to their rapid economic growth, huge population, and large foreign reserves (Chang, 2015; Wang et al., 2016a; Zaman et al., 2016), but also play a crucial role in the global carbon emissions mitigation (Azevedo et al., 2018; Dong et al., 2017; Nassani et al., 2017). According to the statistics of British Petroleum (BP), the carbon dioxide (CO_2) emissions of the BRIICS members reached 14,110 million tonnes (Mt) in 2013, which was about two times compared with the CO_2 emissions of the BRIICS members in 2000 (see Fig.1). Moreover, the BRIICS members have emitted over 40% of world carbon emissions every year since 2009 (BP, 2018).

The substantial carbon emissions have posed a tremendous environmental challenge for the BRIICS (Azevedo et al., 2018; Sebri and Ben-Salha, 2014; Shahbaz et al., 2016). So far the BRIICS have mainly attempted to mitigate environmental degradation from two aspects: (1) to accelerate the development of renewable energy. Renewable energies are cleaner than traditional fossil energies because they emit fewer greenhouse gas from the perspective of the life cycle assessment (Asdrubali et al., 2015; Odeh and Cockerill, 2008). As shown in Fig.1, the renewables energies' consumption in BRIICS kept increasing, as it raised from 180.7 million tonnes of oil equivalent (Mtoe) in 2000 to 437.3 Mtoe in 2013 with an annual growth rate of approximate 7.03%. Besides, the percentage of renewables in energy consumption mix of the BRIICS also kept increasing (see Fig.1). (2) to advance efficiency-enhancing technologies. Technological innovation, especially environmental-related patents can enhance energy efficiency, thus reduce carbon emissions (Voigt et al., 2014; Wurlod and Noailly, 2018). The governments of the BRIICS

Abbreviations: BP, British Petroleum; BRIICS, Brazil, Russia Federation, India, Indonesia, China and South Africa; CEPC, CO_2 emissions per capita; Choi, Choi's modified P Unit-Root; CO_2, carbon dioxide; DCP, domestic credit to private sector; DET, development of environmental-related patents; EKC: Environmental Kuznets Curve; EXP, exports; FDI, foreign direct investment; Fisher, Maddala-Wu Unit-Root ;GDP, gross domestic production; LLC, Levin-Lin-Chu Unit-Root; Mt: million tonnes; Mtoe, million tonnes of oil equivalent; OECD, Organization for Economic Cooperation and Development; OLS, ordinary least square; RES: renewable energy supply; SIC, Schwarz information criterion; TWh, terawatt-hours; VECM, vector error correction model.

[1] The BRIICS originates from the BRICS (namely Brazil, Russia Federation, India, China and South Africa). Typically, the BRICS members are the representatives of the emerging markets. However, Indonesia has developed very well recently, and has expressed strong interest in joining the BRICS. Moreover, the OECD Environment Database that we use proposes the concept of the BRIICS. Therefore, we choose the BRIICS to investigate the impacts of renewable energy, environmental patents and other variables on carbon emission in this paper.

association encourage the development of environmental patents. Consequently, the number of environmental patents of the BRIICS kept increasing except for 2013 (see Fig.1). Although there is a slight decrease in the development of environmental patents in 2013 in the BRIICS, the ratio of the environmental patents developed by the BRIICS to the world's total environmental patents kept increasing from 2% in 2000 to 6.5% in 2013.

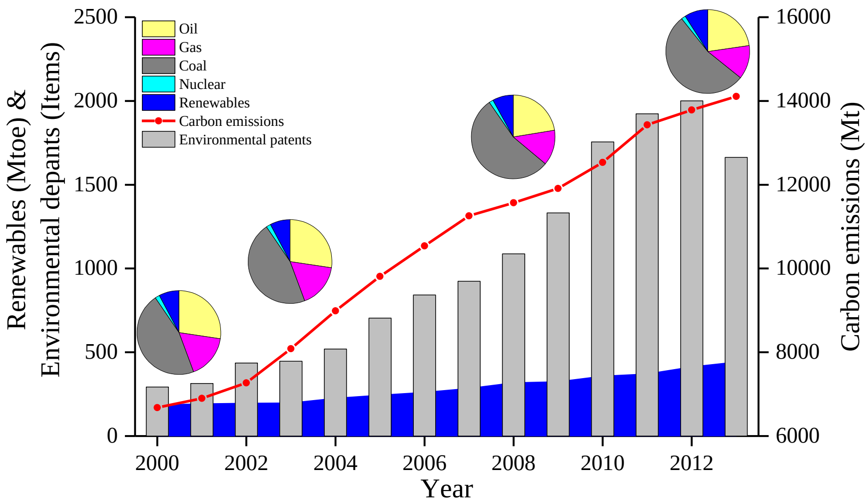


Fig. 1. BRIICS's carbon emissions, energy consumption mix and environmental patents from 2000-2013.
Note: Data are obtained from BP (2018) and the OECD Environment database.

Although the renewable energy consumption and the quantity of environmental patents have increased during the past year in the BRIICS, the CO_2 emissions of the BRIICS countries still raise. Therefore, an investigation, which explores the impacts of renewable energy and environmental patents on carbon emissions, should be conducted to help the BRIICS association to enact climate change policies. Moreover, the traditional panel regression methods applied in the previous literature are usually based on conditional mean methods. Unlike them, we apply the fixed-effect panel quantile regression method proposed by Koenker (2004). As far as we know, no empirical studies have applied the fixed-effect panel quantile regression method to study the carbon emissions issues in the BRIICS countries. Given these motivations, this study investigates the impacts of renewable energy and environmental patents on carbon emission of the BRIICS association by using the annual data from 2000 to 2013[2].

This study contributes to the related literature from two aspects: Firstly, it applies the fixed-effect panel quantile regression method to investigate the impacts of renewable energy supply, environmental patents and other control variables on CO_2 emissions in the BRIICS countries. By applying this method,

[2] The data for environmental patents are available up to 2013.

the problems caused by the overlook of individual heterogeneity and distributional heterogeneity can be solved; moreover, the different effects of the determinant factors across the CO_2 emissions quantiles can be captured. Secondly, it examines the impacts of environmental patents on CO_2 emissions. When exploring the decisive factors of CO_2 emissions, the existing literature focuses on economic growth, energy consumption, renewable energy consumption, foreign direct investment, natural gas and so on, but previous studies neglect technology. To fill this gap, this paper investigates the impacts of environmental patents on carbon emissions.

The remainder of this paper is arranged as follows. Section 2 summarizes the related literature. Section 3 presents the data and empirical methodology adopted in this study. Section 4 describes the empirical results. Section 5 discusses the meaning of these results. Section 6 concludes this paper and provide relevant policy recommendations.

2. Literature review

2.1 The carbon emission and its decisive factors

The first proposition about the relationship between carbon emission and its decisive factors is proposed by Kuznets (1955), and the proposition is the Environmental Kuznets Curve (EKC) hypothesis. In the EKC hypothesis, an inverse U-sharped relationship between CO_2 emissions and economic growth (usually depicted by gross domestic production, GDP) was proposed by Kuznets. Later on, several scholars explored the effects of the economic growth on CO_2 emissions and tested the validity of the EKC hypothesis via empirical studies, such as Selden and Song (1994), Holtz-Eakin and Selden (1995) and Dinda and Coondoo (2006).

Several other determinant factors may affect carbon emissions. These factors include electricity consumption (Cowan et al., 2014), energy consumption (Antonakakis et al., 2017; Wang et al., 2016b), natural gas consumption (Dong et al., 2018; Li and Su, 2017), renewable energy consumption (Cheng et al., 2018; Gozgor, 2018; Sarkodie and Adams, 2018), nuclear energy consumption (Baek, 2016), agriculture (Jebli and Youssef, 2017; Liu et al., 2017a), foreign direct investment (Sarkodie and Strezov, 2019; Zhu et al., 2016), trade openness (Hu et al., 2018; Piaggio et al., 2017), transport service (Nassani et al., 2017), lag of carbon emission (Azevedo et al., 2018), urbanization (Wang et al., 2016a), finance (Nassani et al., 2017) and so on.

These studies explored different determinant factors of carbon emissions, and provided related policy recommendations: (1) to promote the development of renewable energy. Wang et al. (2016b) and Dong et al. (2018)suggested that China should develop renewable energy to reduce emissions. Sarkodie and Adams (2018) recommended that South Africa should diversify its energy portfolio by developing renewable energy. (2) to develop sustainable agriculture. Liu et al. (2017a) suggested that the 4 selected ASEAN countries should develop sustainable agriculture in mitigate CO_2 emissions. (3) to promote the development of the service industry. Sarkodie and Adams (2018) and Wang et al. (2016a) proposed that the governments should shift their economies to a service-oriented economy.

However, the development of environmental patents, which benefits carbon emissions reduction, is usually neglected in previous studies. Few empirical studies examine the influences of environmental patents on carbon emissions by applying econometric methods. Voigt et al. (2014) studied the effects of technology improvement on the reduction of energy intensity, but they applied Logarithmic mean Divisia index decomposition method. Wurlod and Noailly (2018) investigated the contribution of environmental patents to the decrease of carbon emissions by estimating a translog cost function, which is based on the industry's production function. Unlike them, we applied the fixed-effect panel quantile regression method to evaluate the impacts of environmental patents for the BRIICS countries.

2.2 The methodologies applied in studies about the carbon emissions and its decisive factors

The methodologies employed in previous literature is usually based on conditional mean methods, such as ordinary least square (OLS) (Azevedo et al., 2018), panel fully modified OLS (Hu et al., 2018), dynamic OLS (Hu et al., 2018), panel fixed-effect regression (Nassani et al., 2017), vector error correction model (VECM) (Dong et al., 2018; Liu et al., 2017a; Piaggio et al., 2017), autoregressive distributed lag model (Gozgor, 2018; Sarkodie and Adams, 2018), bootstrap panel causality (Cowan et al., 2014), panel vector autoregression (Antonakakis et al., 2017), and vector auto-regression (Li and Su, 2017).

Regarding the carbon emission of the BRICS countries, several scholars applied different econometric methods to explore the impacts of different determinant variables. Azevedo et al. (2018) divided the BRICS countries into two groups and applied the OLS method to investigate the impacts of the lag of carbon emissions. They found that individual heterogeneity existed in the BRICS members. Wang et al. (2016a) applied a panel Granger causality method proposed by Canning and Pedroni (2008) to study the relationship between urbanization and carbon emissions. Cowan et al. (2014) applied bootstrap panel causality methodology to explore the causal effect of electricity consumption on carbon emissions. Dong et al. (2017) employed a VECM to investigate the relationship among CO_2 emissions, renewable energy and natural gas consumptions. Nassani et al. (2017) used panel fixed-effect regression method to examine the impacts of finance, transport, energy and growth factors. Sebri and Ben-Salha (2014) applied the autoregressive distributed lag model and VECM to investigate the causal relationship among economic growth, renewable energy consumption, carbon emissions and trade openness. In summary, previous studies about the BRICS countries usually employed the conditional mean method and did not investigate the impacts of environmental patents on carbon emissions.

However, conditional mean methods can only provide the mean estimation results for the whole panel, and fail to provide a whole picture about the relationship between carbon emissions and related decisive factors. Moreover, conditional mean methods neglect the individual heterogeneity and distributional heterogeneity of the panel data (Koenker, 2004; Sarkodie and Strezov, 2019; Zhu et al., 2016); therefore, they may lead to biased regression results because they ignore both the individual heterogeneity and distributional heterogeneity (Cheng et al., 2018; Zhu et al., 2016). Unlike the conditional mean methods, the panel quantile regression method can estimate the coefficients for different quantiles. Only a few studies applied panel quantile regression methods (Cheng et al., 2018; Sarkodie and Strezov, 2019; Zhu et al., 2016). Cheng et al. (2018) concentrated on the impacts of non-fossil energy, while Sarkodie and Strezov (2019) and Zhu et al. (2016) focused on the impacts of foreign direct investment. Unlike them, in order to thoroughly investigate the impacts of renewable energy supply, environmental patents and other control variables by considering the individual heterogeneity and distributional heterogeneity, we employ the panel quantile regression method proposed by Koenker.

3. Data and Methodology

3.1. Data

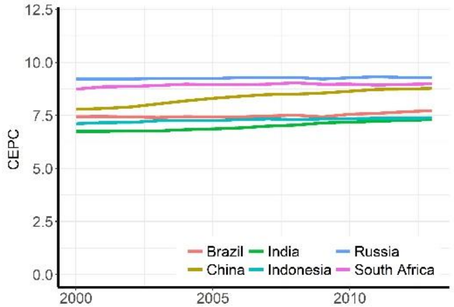
To investigate the impacts of renewable energy supply, environmental patents and other variables on the CO_2 emissions, we collect data from the World Development Indicators (World Bank, 2018) and the Organization for Economic Cooperation and Development (OECD) Environment Database (OECD, 2018) from 2000 to 2013 for the BRIICS members. The sample size is 84. Appendix A summarized the seven variables used in this study, namely CO_2 emissions per capita (denoted by CEPC), renewable energy supply (denoted by RES), development of environment-related technologies (denoted by DET), GDP per capita (denoted by GDP), exports of goods and services (denoted by EXP), foreign direct investment (denoted by FDI) and domestic credit to private sector (denoted by DCP).

CO_2 emissions per capita (CEPC) represents the units of CO_2 emissions from the combustion of primary energy (such as coal, crude oil, natural gas and other fuels) divided by population. Fig. 1a depicts the time series of the CEPC (after logarithm) for the six BRIICS countries. The CEPC of Russia is the highest among the six BRIICS countries, while India produces the lowest CEPC. Fig.1a indicates that the distributions of CEPC in different countries are diverse.

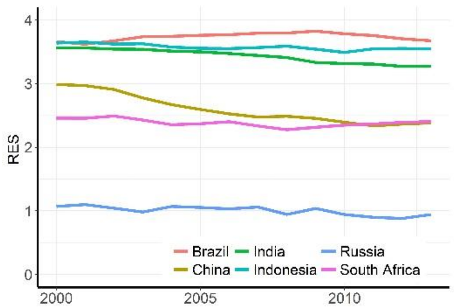
Renewable energy supply (RES) is denoted as the ratio of renewable energy supply to the aggregate primary energy supply. Renewable energies include geothermal, solar energy, combustible renewables, wind and so on. Fig. 1b reveals the time series of the RES (after logarithm) for the six BRIICS countries. Overall, Brazil, Indonesia and India have higher RES than China, Russia and South Africa. According to OECD environmental database, the average ratio of renewable energy supply to the primary energy supply in Brazil was approximate 42.0% from 2000 to 2013, the ratios in Indonesia and India were about 35.7% and 31.3%, respectively. However, the ratios of renewable energy supply in China, Russia and South Africa were much less, and were only about 13.7%, 2.73% and 10.9%, respectively.

Development of environment-related technologies (DET) represents creative activity. Specifically, it depicts the patent which belongs to environment-related technological domains, including environmental management, water-related adaptation, and climate change mitigation technologies. Patent counts are used to represent the innovative activity in previous literature (Hagedoorn and Cloodt, 2003; Popp, 2005; Wurlod and Noailly, 2018). The number of environment-related inventions is expressed as items per million residents (higher-value inventions/million persons). Fig. 1c shows the time series of the DET (after logarithm) for the six BRIICS countries. As shown in Fig. 1d, the DET in Russia and South Africa was kept at a high level during our sample period, while the DET in China and India was at a low level initially but kept increasing rapidly.

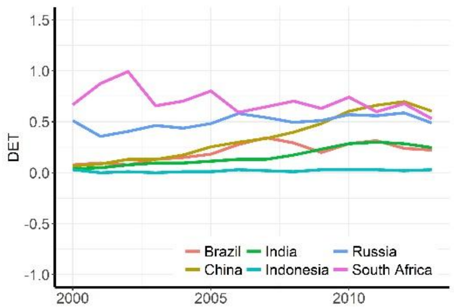
GDP per capita (GDP) measures a country's economic wealth of the population of a nation and is expressed at constant 2010 USD PPP prices. GDP per capita also implies the economic growth of a nation. Moreover, economic growth is widely recognized as an essential factor for CO_2 emission in previous research (Kuznets, 1955; Sarkodie and Strezov, 2019; Selden and Song, 1994). Fig. 1d shows the series of the GDP (after logarithm) for the six BRIICS countries. Russia is the wealthiest country, while India is



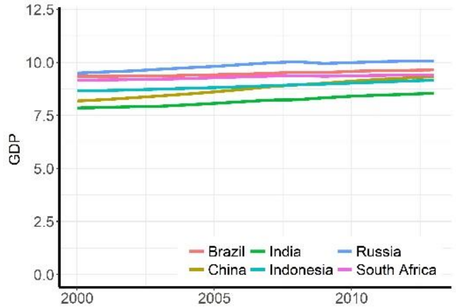
(a) carbon emission per capita



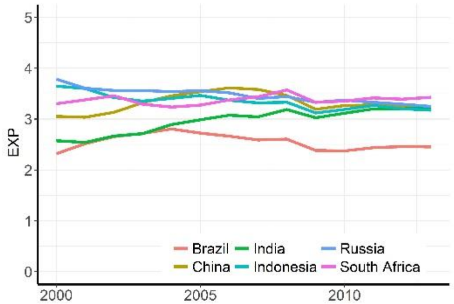
(b) renewable energy supply



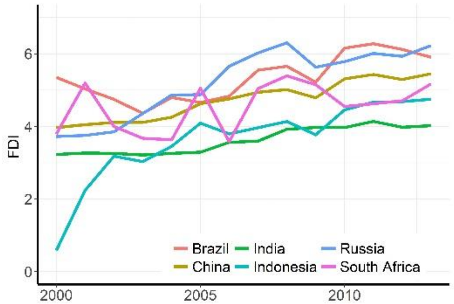
(c) development of environmental patents



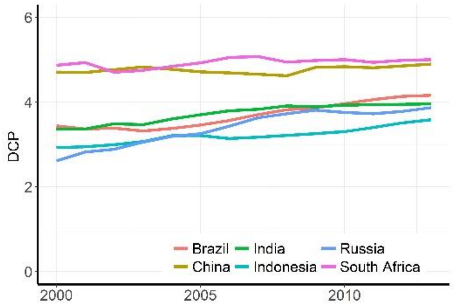
(d) GDP per capita



(e) exports of goods and services



(f) foreign direct investment



(g) domestic credit to private sector

Fig.2. The trends of the CEPC, RES, DET, GDP, EXP, FDI and DCP in the six BRIICS countries over 2000–2013 (after logarithm).

the poorest county among BRIICS.

Exports of goods and services (EXP) denotes the total value of all goods and services which are sold to the other countries. The EXP is used to reveal the role of international trade in a nation; it influences a nation's carbon emissions (Hu et al., 2018; Piaggio et al., 2017). Therefore, it is used as a control variable in this study. Fig. 1e reveals the time series of the EXP (after logarithm) for the BRIICS countries. As shown in Fig. 1e, the EXP is very important for the BRIICS countries as the EXP accounted a large percent in their GDP.

Foreign direct investment (FDI) measures the inward investment volumes provided by non-resident investors. It affects the carbon emissions of a nation: (1) In the pollution heaven hypothesis, the FDI may aggravate the carbon emissions as the host countries welcome any kinds of investment, including the investment which may cause serious pollutions. (2) In the halo effect hypothesis, the FDI may mitigate the carbon emissions because the host countries can introduce environmental-friendly technologies (Sarkodie and Strezov, 2019; Zhu et al., 2016). Considering the impacts of the FDI, we use it as another control variable in this study. The time series of the FDI (after logarithm) for the six BRIICS countries are depicted in Fig. 1f. Overall, the fluctuation of the FDI flows is large. Compared with India, Indonesia and South Africa, Brazil, Russia and China have more FDI volumes.

Domestic credit to private sector (DCP) represents the value of domestic funds lent to the private sector by financial corporations, representing a country's domestic financial investment. Following Nassani et al. (2017), we use DCP as another control variable in our study. The time series of the DCP (after logarithm) is depicted in Fig. 1g. The DCP in China and South Africa is larger than the DCP in other BRIICS countries.

Before conducting the empirical analysis, all variables are transformed into natural logarithms. Table 1 presents a summary of the statistical description for the seven variables, including the minimum value, maximum value, 25th quantile, 75th quantile, mean value, standard deviation, skewness, kurtosis and Jarque–Bera test. The skewness values and the kurtosis values in Table 1 indicate that all the seven variables are not normally distributed. Moreover, the results of Jarque–Bera statistical test also imply that these series depart from normal distributions (except GDP). Overall, the results imply that the OLS method is not suitable for these series, providing supports for the panel quantile regression methods we apply.

Table 1. Summary statistics.

Variable	ln(CEPC)	ln(RES)	ln(DET)	ln(GDP)	ln(EXP)	ln(FDI)	ln(DCP)
Minimum	6.7503	0.8810	0.0000	7.8572	2.3212	0.5844	-0.8911
Maximum	9.3257	3.8243	0.9933	10.0771	3.7856	6.3016	2.1949
1. Quartile	7.3095	2.3657	0.0930	8.6724	3.0341	3.8345	1.4214
3. Quartile	8.9534	3.5636	0.5466	9.4570	3.4184	5.1977	1.8642
Mean	8.0527	2.7877	0.3232	9.0775	3.1700	4.5080	1.6039
Stdev	0.8736	0.9531	0.2560	0.5848	0.3604	1.0055	0.4019
Skewness	0.1455	-0.7992	0.4457	-0.3491	-0.8179	-0.5551	-3.2555
Kurtosis	-1.6084	-0.6456	-0.9565	-0.7481	-0.3934	1.2901	16.661
Jarque–Bera	8.9859***	10.481***	5.7624**	3.4512	10.089***	11.274***	1181.8***

*significant at 10% level

**significant at 5% level

***significant at 1% level

3.2. Panel quantile regression

In this subsection, we briefly introduce a fixed-effect panel quantile regression model proposed by Koenker (2004). Fixed-effect and separate disturbance terms are considered in this panel quantile regression model. This panel quantile regression method is different from another panel quantile regression method applied by Sarkodie and Strezov (2019). The panel quantile method applied by Sarkodie and Strezov does not consider the fixed-effect and assumes a non-separable disturbance term in the model.

In general, the conditional mean regression method can provide unbiased results if the error follows the normal distribution. However, the normality assumption is hardly satisfied in empirical studies. As mentioned in Section 3.1, the variables in this study do not conform to the normality assumption. In this case, the conditional mean regression may yield biased coefficients, or fails to provide reliable relationships (Ren et al., 2019; Zhu et al., 2016). Moreover, individual heterogeneity is also neglected in the conditional mean regression method. Therefore, in order to overcome these shortcomings of the conditional mean regression method, the quantile regression method is proposed by Koenker and Bassett (1978), and is adopted by many scholars.

The fixed-effects panel quantile model is expressed as:

$$Q_{Y_{i,t}}\left(\tau \middle| X_{i,t}\right) = \alpha(\tau)' X_{i,t} + \beta_i,\ i = 1, \dots, N, t = 1, \dots, T \quad (1)$$

where $Y_{i,t}$ denotes the dependent variables (CEPC), $X_{i,t}$ represents the independent variables (RES, DET, GDP, EXP, FDI and DCP), $\alpha(\tau)$ denotes the unknown coefficients, β_i represents the unobserved individual effects. i denotes the BRIICS countries, t denotes the year. Specifically, the model in this paper is:

$$Q_{Y_{i,t}}(\tau|X_{i,t}) = \alpha_{1,\tau}\mathrm{RES}_{i,t} + \alpha_{2,\tau}\mathrm{DET}_{i,t} + \alpha_{3,\tau}\mathrm{GDP}_{i,t} + \alpha_{4,\tau}\mathrm{EXP}_{i,t} + \alpha_{5,\tau}\mathrm{FDI}_{i,t} + \alpha_{6,\tau}\mathrm{DCP}_{i,t} + \beta_i,$$

$$i = 1, \dots, N, t = 1, \dots, T \qquad (2)$$

The main problem about estimating model (2) is that traditional linear approaches are unfeasible in the quantile regression model. To address such problems, Koenker (2004) introduced a penalty term in the minimization process, which can eliminate unobserved fixed-effects[3]. Compared with other methods, this method has two advantages: (1) it can control the variability caused by a lot of estimated individual coefficients; (2) it can effectively reduce the number of estimated parameters. Following Koenker, we estimate Equation (2) by using the specific model as follows:

$$\underset{\alpha}{\operatorname{argmin}} \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{t=1}^{T} w_k \rho_{\tau_k}\{Y_{i,t} - \alpha_{1,\tau}\mathrm{RES}_{i,t} - \alpha_{2,\tau}\mathrm{DET}_{i,t} - \alpha_{3,\tau}\mathrm{GDP}_{i,t} - \alpha_{4,\tau}\mathrm{EXP}_{i,t} - \alpha_{5,\tau}\mathrm{FDI}_{i,t}$$

$$- \alpha_{6,\tau}\mathrm{DCP}_{i,t} - \beta_i\} + \mu \sum_{i=1}^{N} |\beta_i|$$

$$i = 1, \dots, N, t = 1, \dots, T \qquad (3)$$

where $\rho_\tau(y) = y(\tau - \mathbf{1}_{y<0})$ is the traditional check function, $\mathbf{1}_A$ is the indicator function of set A. $Y_{i,t}$ denotes the carbon dioxide emission per capita in country *i* at time *t*. *K* is the index for quantiles, and w_k (which equals to $1/K$) is the weight of *k*-th quantile, controlling the relative importance of different quantiles in this estimation (Alexander et al., 2011; Lamarche, 2011; Zhu et al., 2016). μ is the tuning parameter to control the individual effects. Like Damette and Delacote (2012) and Zhu et al. (2016), we assume that μ equals to 1 in this paper.

4. Empirical results and discussion

4.1. Panel unit root test

Before estimating the coefficients, we use several panel unit root tests to check whether the variables are stationary. To be specific, these tests consist of the Levin-Lin-Chu Unit-Root (denoted as LLC) Test (Levin et al., 2002), Choi's modified P Unit-Root (represented by Choi) Test (Choi, 2001), Maddala-Wu Unit-Root (denoted as Fisher) Test (Maddala and Wu, 1999), Hadri Test (Hadri, 2000), and IPS test (Im

[3] Koenker (2004) consider $N = 5$ in the finite sample behavior of the penalized quantile regression and get accurate estimator. In this research, our sample contains 6 countries ($N = 6$), which is similar to the monte carlo simulation in Koenker (2004).

et al., 2003). The results of these panel unit root tests are listed in Table 2, and the results indicate that all the variables are stationary at levels. Therefore, these is no need to conduct these tests at first difference and to conduct cointegration test. We conduct the panel regression model and panel quantile regression model at levels.

Table 2. Results of panel unit root tests.

Variable	ln(CEPC)	ln(RES)	ln(DET)	ln(GDP)	ln(EXP)	ln(FDI)	ln(DCP)
LLC	-4.2301***	-2.8789***	-3.273***	-2.8576***	-2.9053***	-3.4056***	-2.4639***
Choi	12.465***	2.5694***	10.751***	2.4332***	13.399***	4.8911***	16.828***
Fisher	65.96***	38.128***	64.67***	93.651***	77.643***	35.961***	94.438***
Hadri	15.521***	13.197***	12.013***	9.414***	5.8102***	14.508***	14.664***
IPS	-2.329***	-2.2827***	-3.3844***	-3.4959***	-3.5094***	-3.518***	-3.3758***

Note: The maximum number of lags is set to four. The Schwarz information criterion (SIC) is used to select the lag length.
*significant at 10% level
**significant at 5% level
***significant at 1% level

4.2. Panel regression results

To compare the OLS regression method with the panel quantile regression method, this paper first conducts three conditional mean regression methods – the pooled OLS model, the OLS one-way fixed-effect model and the OLS two-way fixed-effect model. The regression results are presented in Table 3, indicating almost all the coefficients in our model are statistically significant at 10% level.

Table 3. OLS regression results

Variable	Pooled OLS	OLS one-way fixed-effect	OLS two-way fixed-effect
Intercept	2.0864***	4.6812***	7.3437***
	(0.4554)	(0.9362)	(1.5119)
ln(RES)	-0.5382***	-0.4787***	-0.5967***
	(0.0274)	(0.1128)	(0.1317)
ln(DET)	0.1712	0.1290*	0.2638***
	(0.1137)	(0.0712)	(0.0900)
ln(GDP)	0.6396***	0.5152***	0.2703**
	(0.0461)	(0.0842)	(0.1336)
ln(EXP)	0.1682***	0.1071***	0.0940**
	(0.0581)	(0.0372)	(0.0469)
ln(FDI)	-0.1160***	0.0059	0.0029
	(0.0255)	(0.0129)	(0.0157)
ln(DCP)	0.4034***	-0.0957**	-0.1209**
	(0.0340)	(0.0419)	(0.0460)

Figures in parentheses are standard error.
*significant at 10% level
**significant at 5% level
***significant at 1% level

The relationships between RES and CEPC in the three conditional mean regression models are presented in Table 3. In these three models, RES has a negative impact on carbon emissions: one more unit of RES reduces CEPC by 0.5382, 0.4787 and 0.5967 unit, respectively. The results imply that renewable energy is beneficial for carbon mitigation. This effect is also observed by Nassani et al. (2017) and Dong et al. (2017), who confirm that renewable energy can reduce carbon emissions in BRICS. Moreover, the results also coincide with Liu et al. (2017a), who confirms that renewable energy can reduce carbon emission in Indonesia.

The impact of DET on CO_2 emissions is positive in the three conditional mean regression models (see Table 3). Specifically, one more unit of DET increases CEPC by 0.1712 unit in the pooled OLS model, but the impact is not significant. However, in the OLS one-way fixed-effect model and OLS two-way fixed model, one more unit of DET significantly increases CEPC by 0.129 and 0.2638 unit, respectively. Thus, we find an increasing effect of DET on the CEPC in the three conditional mean regression model, indicating that the development of environmental patents increases carbon emissions in the BRIICS countries.

Moreover, the positive impacts of GDP and EXP on carbon emission are evidenced in Table 3. These results are supported by Dong et al. (2017), who prove that GDP has a positive impact on carbon emission in BRICS, but contrary to Hu et al. (2018), who confirm a negative impact of exports on carbon emission in 25 developing countries including the six BRIICS countries.

With regards to FDI and DCP, the results of the three conditional mean regression method are mixed. To be specific, a significant negative effect of FDI on the CO_2 emissions is observed in the pooled OLS model, while an insignificant positive impact of FDI on the carbon emissions is presented in the OLS one-way and two-way fixed-effect model. As for DCP, a significant positive impact is evidenced in the pooled OLS model, while a significant negative impact is provided in the OLS one-way and two-way fixed-effect model. One possible explanation for the inconsistent results is that the OLS method neglects the individual heterogeneity and distributional heterogeneity in the panel data (Cheng et al., 2018; Zhu et al., 2016). Therefore, the panel quantile regression method should be used to provide a more explicit relationship between carbon emissions and the decisive factors.

4.3. Panel quantile regression results

In this subsection, we use the panel quantile regression method to reflect the limitation of the conditional mean regression method. The heterogeneous impacts of RES, DET, GDP, EXP, FDI and DCP on the CEPC are estimated with the fixed-effect panel quantile regression method and presented in Table 4 and Fig. 3. The results are reported for the 5th, 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th and 95th percentiles of the conditional carbon dioxide emission per capita. The regression results in Table 4 and Fig. 3 reveal that the impacts of various factors on CEPC are heterogeneous.

The impact of renewable energy supply on carbon dioxide emission per capita is heterogeneous and significant at 1% level. The ln(RES) row of Table 4 demonstrates that RES decreases CEPC in all quantiles, but the impacts of RES on CEPC are asymmetric through different quantiles. To be specific, the coefficients of RES have a decreasing trend in different quantiles, from -0.419 in the 10th quantile to -0.601 in the 95th quantile. In other words, the mitigation impacts of RES on CEPC increase across the quantiles. The aggregate effect[4] of RES on CPEC is consistent with the conditional mean regression results in Table 3.

The impact of the development of environmental patents on CO_2 emission per capita is heterogeneous. In the ln(DET) row of Table 4, CEPC increases with a promotion in the development of environmental patents. Moreover, the impacts of DET on CEPC have an increasing trend. The coefficients of ln(DET) increase from 0.0284 in the 5th quantile to 0.3395 in the 80th quantile, then decrease slightly, and reduce to 0.2518 in the 95th quantile. However, only the coefficient in the 95th quantile is significant. The aggregate weight of DET on CEPC agrees with the conditional mean regression results in Table 3.

The impact of GDP per capita on carbon emission per capita is clearly heterogeneous and significant at 1% level. The ln(GDP) row in Table 4 shows that GDP increases CEPC at all quantiles, but its impacts in different quantiles are different. To be specific, the coefficients of ln(GDP) first decrease from 0.76 in the 5th quantile to 0.6355 at the 60th quantile, and stabilize around 0.6. Nevertheless, the aggregate effect of GDP on CEPC is in line with the conditional mean regression results in Table 3.

The effect of exports on carbon emissions per capita is heterogeneous. The ln(EXP) row in Table 4 implies that CEPC asymmetrically increases with increasing exports across all quantiles. Specifically, the impacts are the strongest at the lower quantiles, which was about 0.39, then the impacts decrease from 0.3964 in the 30th quantile to 0.1587 in the 70th quantile, and becomes stable in the upper tail of the

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[4] Aggregate effect (weight) denotes the aggregate impacts of the decisive factors across different CO_2 quantiles.

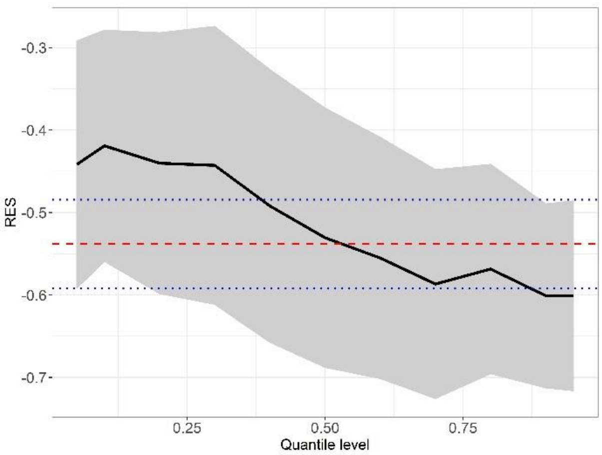
conditional CEPC distribution. Moreover, the coefficients are significant for all quantiles except for 5th and 70th quantiles. The aggregate weight of EXP on CEPC agrees with the regression results in Table 3.

The impact of foreign direct investment on carbon emissions per capita is heterogeneous. The regression results of the ln(FDI) row in Table 4 indicates that an increase in FDI can lead to a decrease in CPEC. Again, the impacts are asymmetric, the coefficients increase slightly at the lower quantiles, then decrease to -0.1329 in the 50th quantile, and increase thereafter. The negative impacts of FDI decrease slightly at the beginning, then accelerate until the 50th quantile, and decline from the 50th quantile. Moreover, the coefficients are non-significant at lower quantiles, then become significant at the high quantiles.The aggregate effect of FDI on CEPC is inconsistent with the results in Table 3.

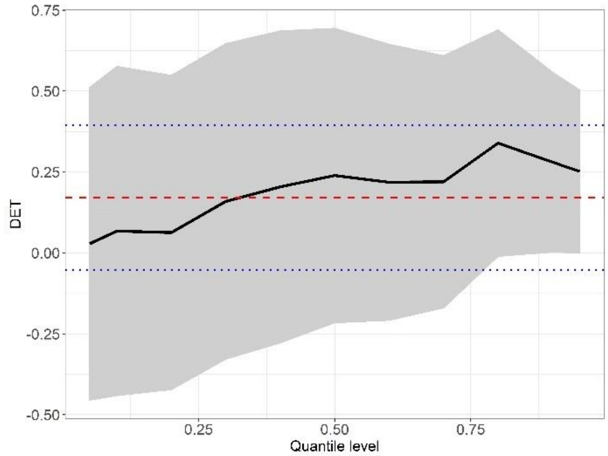
The impact of domestic financial development on CO_2 emissions per capita is heterogeneous and significant at 1% level. The ln(DCP) row in Table 4 shows that CEPC increases with increasing domestic credit to the private sector, but the impacts have a declining trend. Specifically, the coefficients decrease from 0.5346 in the 5th quantile to 0.3471 in the 95th quantile.The aggregate weight of DCP on CEPC is consistent with the results of OLS regression in Table 3.

In brief, by comparing the results of the three OLS methods and the fixed-effect panel quantile regression method, we conclude that the panel quantile regression with fixed-effects can provide a complete relationship about the effects of RES, DET, GDP, EXP, FDI and DCP on CEPC in six BRIICS countries. These regression results reveal that the decisive factors have clear heterogeneous impacts on CEPC. In particular, RES reduces CEPC with the strongest effect in the 95th quantile. DET accelerates CEPC, but only significantly affects the CEPC at the upper tail of the conditional distribution. GDP enhances CEPC with the strongest effect in the 5th quantile. EXP increases CEPC with an asymmetric inverted U-sharped impact. FDI declines CEPC, but only significantly influences the CEPC at the medium and upper of the conditional distribution. DCP raises CEPC with gradually decreasing impacts along with all the quantiles.

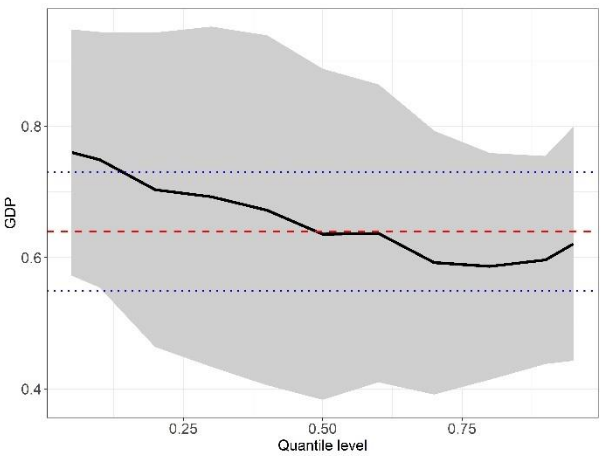
We proceed with a robustness check to further test the validity of the regression results. The robustness check mainly considers different values for μ. To be specific, we conduct the panel quantile regression by using different μ, namely 0.1, 0.9 and 2.0. The results are presented in Table 5, in which we only present the results of RES, GDP and EXP to save space. The results of the three different μ are consistent with the results presented in Table 4. Therefore, the robustness check indicates our results are robust and reliable.



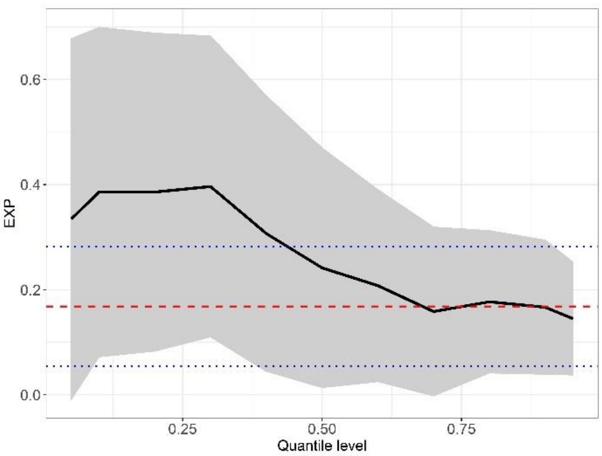
(a) *RES*



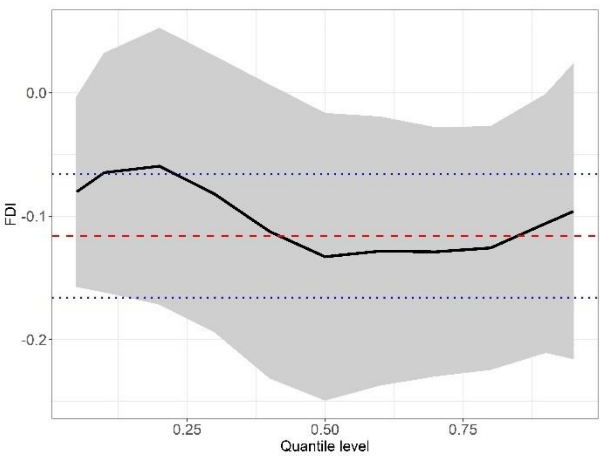
(b) *DET*



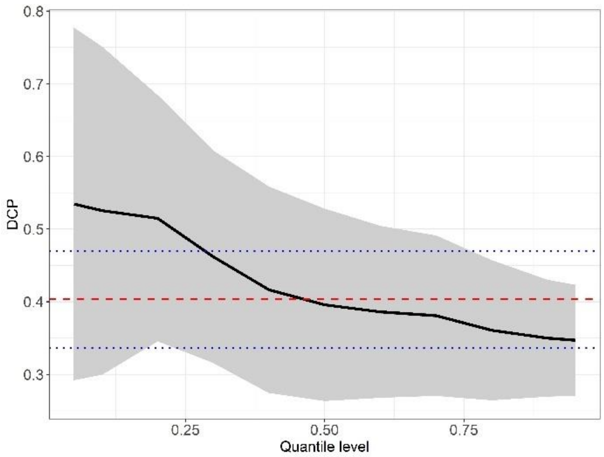
(c) *GDP*



(d) *EXP*



(e) *FDI*



(f) *DCP*

Fig. 3. Change in panel quantile regressions coefficients.

Notes: Shaded areas correspond to 95% confidence intervals of quantile estimation. The red dashed line represents the corresponding OLS estimate with its 95% confidence interval (blue dashed line).

Table 4. Panel quantile regression results.

Coefficients	Quantiles										
	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
Intercept	-0.5419	-0.7001	-0.1690	0.2270	1.1885	2.0278	2.2388***	2.9352***	2.9294***	2.9701***	2.8134***
	(-0.3442)	(-0.4818)	(-0.1177)	(0.1673)	(0.9139)	(1.7609)	(2.2010)	(3.1136)	(3.4353)	(3.6308)	(3.1453)
ln(RES)	-0.4417***	-0.4190***	-0.4401***	-0.4427***	-0.4920***	-0.5305***	-0.5551***	-0.5867***	-0.5685***	-0.6009***	-0.6010***
	(-5.7749)	(-5.8596)	(-5.4527)	(-5.1478)	(-5.8316)	(-6.6135)	(-7.4367)	(-8.2871)	(-8.7747)	(-10.5518)	(-10.2368)
ln(DET)	0.0284	0.0678	0.0631	0.1593	0.2042	0.2393	0.2183	0.2199	0.3395	0.2808*	0.2518*
	(0.1154)	(0.2612)	(0.2546)	(0.6403)	(0.8304)	(1.0312)	(1.0034)	(1.1058)	(1.9015)	(1.9799)	(1.9604)
ln(GDP)	0.7600***	0.7489***	0.7031***	0.6927***	0.6721***	0.6355***	0.6369***	0.5922***	0.5866***	0.5963***	0.6208***
	(7.9756)	(7.5731)	(5.7719)	(5.2564)	(4.9596)	(4.9570)	(5.5207)	(5.8033)	(6.6935)	(7.4132)	(6.8680)
ln(EXP)	0.3343	0.3858*	0.3856 **	0.3964**	0.3068*	0.2417*	0.2078*	0.1587	0.1770**	0.1668**	0.1449**
	(1.9097)	(2.4131)	(2.4995)	(2.7154)	(2.2951)	(2.0785)	(2.2311)	(1.9374)	(2.5645)	(2.5636)	(2.6523)
ln(FDI)	-0.0804*	-0.0647	-0.0596	-0.0822	-0.1126	-0.1329*	-0.1283*	-0.1289**	-0.1258**	-0.1059*	-0.0961
	(-2.0532)	(-1.3131)	(-1.0450)	(-1.4440)	(-1.8606)	(-2.2425)	(-2.3167)	(-2.5133)	(-2.5080)	(-1.9856)	(-1.5786)
ln(DCP)	0.5346***	0.5254***	0.5149***	0.4619***	0.4165***	0.3958***	0.3862***	0.3809***	0.3608***	0.3499***	0.3471***
	(4.3342)	(4.5772)	(5.9860)	(6.2217)	(5.7807)	(5.8924)	(6.4363)	(6.8034)	(7.3925)	(8.6033)	(8.9825)

Note: Numbers in the parentheses represent t-statistics.
*significant at 10% level
**significant at 5% level
***significant at 1% level

Table 5. Robustness analysis: Alternative values of μ.

	Variable	Quantiles										
		0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95
μ = 0.1	ln(RES)	-0.4396	-0.4214	-0.4392	-0.4397	-0.4971	-0.5347	-0.5526	-0.5842	-0.5673	-0.5991	-0.5968
		(0.0022)	(0.0022)	(0.0023)	(0.0024)	(0.0010)	(0.0004)	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	ln(GDP)	0.7636	0.7489	0.7045	0.6830	0.6823	0.6412	0.6270	0.5854	0.5877	0.5939	0.6207
		(0.0003)	(0.0005)	(0.0014)	(0.0024)	(0.0023)	(0.0026)	(0.0016)	(0.0010)	(0.0008)	(0.0006)	(0.0005)
	ln(EXP)	0.3468	0.3896	0.3939	0.4137	0.2998	0.2386	0.2186	0.1659	0.1785	0.1726	0.1509
		(0.1460)	(0.1101)	(0.1063)	(0.0663)	(0.1315)	(0.1689)	(0.1410)	(0.1225)	(0.0456)	(0.0378)	(0.0413)
μ = 0.9	ln(RES)	-0.4417	-0.4190	-0.4401	-0.4427	-0.4920	-0.5305	-0.5551	-0.5867	-0.5685	-0.6009	-0.6010
		(0.0020)	(0.0023)	(0.0029)	(0.0030)	(0.0018)	(0.0007)	(0.0004)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
	ln(GDP)	0.7600	0.7489	0.7031	0.6927	0.6721	0.6355	0.6369	0.5922	0.5866	0.5963	0.6208
		(0.0002)	(0.0002)	(0.0011)	(0.0020)	(0.0023)	(0.0024)	(0.0013)	(0.0008)	(0.0006)	(0.0005)	(0.0002)
	ln(EXP)	0.3343	0.3858	0.3856	0.3964	0.3069	0.2417	0.2078	0.1587	0.1770	0.1668	0.1449
		(0.1262)	(0.0824)	(0.0866)	(0.0584)	(0.1001)	(0.1173)	(0.0951)	(0.1223)	(0.0616)	(0.0375)	(0.0607)
μ = 2	ln(RES)	-0.4427	-0.4179	-0.4405	-0.4443	-0.4896	-0.5286	-0.5572	-0.5853	-0.5690	-0.6018	-0.6030
		(0.0012)	(0.0013)	(0.0017)	(0.0020)	(0.0009)	(0.0004)	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	ln(GDP)	0.7583	0.7489	0.7025	0.7017	0.6674	0.6309	0.6444	0.5929	0.5861	0.5974	0.6208
		(0.0003)	(0.0004)	(0.0014)	(0.0015)	(0.0020)	(0.0019)	(0.0009)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
	ln(EXP)	0.3285	0.3840	0.3818	0.3822	0.3101	0.2447	0.1983	0.1608	0.1763	0.1641	0.1421
		(0.1282)	(0.0832)	(0.0985)	(0.0739)	(0.1004)	(0.1245)	(0.1357)	(0.1134)	(0.0545)	(0.0392)	(0.0452)

Note: Numbers in the parentheses represent p-value.

5. Discussion

5.1. The analysis of renewable energy supply and carbon emissions per capita

All regression results reveal that renewable energy supply has a negative impact on carbon emissions per capita. This result is consistent with Dong et al. (2017) and Nassani et al. (2017), who find that renewable energy consumption is negatively related to CO_2 emissions. Moreover, this finding is also similar to Hu et al. (2018) who find that increasing share of renewable energy contributes to carbon emission reduction in 25 developing countries, which includes the BIIRCS countries. The life cycle CO_2 emissions of renewable energy are much fewer than the counterpart of fossil energy (Dong et al., 2017). Moreover, all BRIICS countries are promoting the development of renewable energy. Specifically, the renewable energy production in the BRIICS countries had increased from 19.72 terawatt-hours (TWh) in 2000 to 300.67 TWh, with an average annual growth rate of approximate 23.31%. The rapid development of renewable energy strengthens the reduction effect of renewable energy on carbon emissions. Due to these two reasons, the expansion of renewable energy can greatly reduce the carbon emissions in the BRIICS countries.

With respect to the heterogeneous impacts of RES, the regression results indicate that the negative impact of RES is greater for high CEPC quantiles than the counterpart for low CEPC quantiles. The possible reason may be that the RES has a diminishing marginal effect on CEPC. To be specific, the high quantiles of CEPC represent the samples with high CEPC. A typical sample is the Russia Federation. In Russia, the RES only accounted for a small portion of the total energy supply because oil and gas are very abundant. Meanwhile, the low quantiles depict the samples with low carbon emissions per capita, like Brazil. Renewable energy takes a crucial position in Brazil's energy supply mix. Compared with the Russia Federation, Brazil has already seen the rapid development of renewable energy. The related equipment and technology are very sophisticated, even the scale economies in the renewable energy sector may be achieved. However, as the development of renewable energy sector is still at the early stage in Russia, the most advanced equipment and techniques can be imported and applied in Russia due to the halo effect of FDI (this supposition is supported by the negative impacts of FDI). Therefore, the reduction effects of RES are greater for Russia than that for Brazil. Moreover, along with the development of the renewable energy industry, the economies of scale may even enlarge the difference of renewable energy' negative impacts.

5.2. The analysis of environmental patents and carbon emissions per capita

Although not all the regression results are statistically significant, all results reveal that the development of environmental patents has a positive impact on carbon emissions per capita. The results are counterintuitive. A possible explanation is the lack of environmental regulation. Environmental regulation, especially market-based regulation, is proved to have significant positive impacts on the improvement of eco-efficiency (including carbon reduction) (Ren et al., 2018; Zhao et al., 2015). Moreover, it significantly promotes the development of technologic innovation (Guo et al., 2017). Thus, environmental regulation is crucial because it is the linkage between carbon mitigation and technological innovation and can bring environmental-related patents to the market. Environmental regulation, or the government interface, is recognized as an important policy to make sure the environmental-related patents can be properly applied (Wang et al., 2012). Apart from the lack of environmental regulation, there are other factors that impede the diffusion of sophisticated technologies related to carbon mitigation, like the restriction of technology transmission, the high application fees of patents and the intellectual property rights (Mensah et al., 2018). In summary, the obstacles which prohibit the carbon mitigation technologies from being applied all over the world is the main reason that causes the positive impacts of environmental-related patents on carbon emissions.

5.3. The analysis of economic growth and carbon emissions per capita

All the regression results indicate that GDP per capita has a positive impact on carbon emissions per capita. The results are similar to the results of Dong et al. (2017), Hu et al. (2018) and Sarkodie and Strezov (2019), but contrary to the results of Liu et al. (2017b). The positive impacts imply that a raise in GDP per capita will lead to more CEPC. The results can be explained by EKC. According to the EKC hypothesis, economic growth enhances carbon emissions during the industrialization process of an economy. Specifically, industrialization needs massive natural resources, especially energy. Excessive consumption of natural resources could cause the ecological deficit and serious environmental problems (Sarkodie and Strezov, 2019). While as the economy continues to grow, the country will experience a period of post-industrialization. In the post-industrial period, environmental protection awareness, laws and regulations and economic structure towards the tertiary sector could result in a reduction in carbon emissions.

These six BRIICS countries are developing countries and still experience the industrialization period. The secondary sector, especially the industrial sector, is still one of the driven forces of economic development in the BRIICS countries. According to the World Bank database, the value added of industry (including construction) accounted for more than 21.22% of the total GDP in 2013 for the BRIICS countries. Specifically, the value added of industry take more than 40% in China and Indonesia. During the process from developing countries to developed countries, economic growth would deteriorate the carbon emissions. This supposition is also supported by the positive impacts of domestic credit to the private sector on carbon emissions.

5.4. The analysis of exports and carbon emissions per capita

All the regression results reveal that exports have a positive impact on carbon emission per capita in the BRIICS countries. Our results are contrary to that of Hu et al. (2018), who found a negative impact of EXP on carbon emissions for 25 developing countries. The possible explanation is that the BRIICS countries are still located at the low position at the global production chain due to the lack of sophisticated technology and elaborate design, thus they only manufacture or assemble products which are designed by other countries (like China, Indonesia and India), or export natural resources (like Russia and South Africa). During the manufacture process of industrial products and the exploration process of natural resources, CO_2 is emitted in the BRIICS countries, while the produced products or natural resources are used by the importers (this issue is called the embodied carbon dioxide emission) (Chen and Chen, 2011; Meng et al., 2018). This kind of export would cause serious damage to the environment of the BRIICS countries. Therefore, an increase in EXP in the BRIICS countries would lead to more carbon emissions.

5.5. The analysis of foreign direct investment and carbon emissions per capita

The regression results indicate that foreign direct investment (FDI) has a negative impact on carbon emission per capita. The results are consistent with Sarkodie and Strezov (2019), who investigated the FDI's impact on carbon emissions in developing countries. Besides, the results are also supported by Atici (2012) and Zhu et al. (2016), who found FDI has a negative impact on carbon emissions in the Association of Southeast Asian Countries (which includes Indonesia). The negative impacts of FDI on the carbon emissions can be explained by the halo effect hypothesis. As the governments in the BRIICS association pays more attention to environmental problems, they encourage foreign investors to disseminate their specialized technologies and practical management skills in the BRIICS countries. Moreover, transnational corporations also tend to transfer their technologies and management skills to the companies in the host countries, and help them to mitigate the negative impacts of carbon emissions. Therefore, FDI has a negative impact on carbon emissions.

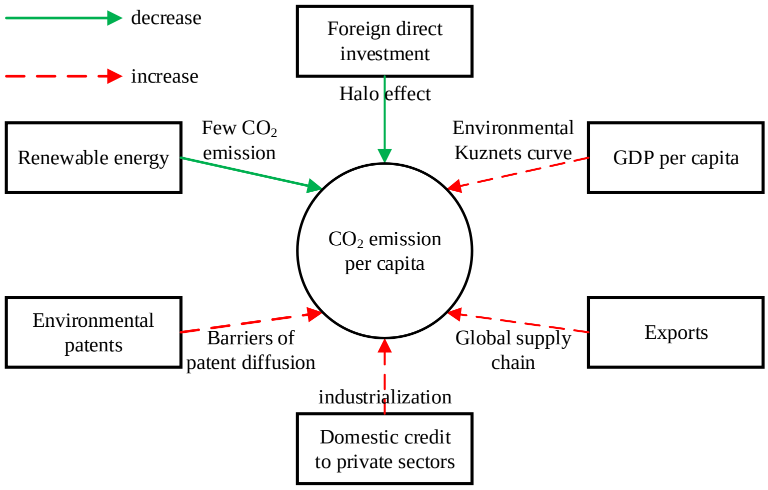
5.6. The analysis of domestic credit to the private sector and carbon emissions per capita

The regression results imply that domestic credit to the private sector has a negative impact on carbon emission per capita. The results are supported by Nassani et al. (2017), who demonstrated that DCP deteriorated environmental quality in the BRICS countries. One possible explanation is that the BRIICS members are still experiencing the period of industrialization. Therefore, the secondary sector plays a crucial role in economic development. However, the development of secondary sector relied on energy. Meanwhile, the fossil energy accounted for a large proportion in the primary energy supply mix in the BRIICS countries. Moreover, the DCP is usually applied in the secondary sector in the BRIICS countries. Therefore, a rise in DCP could lead to larger carbon emissions.

6. Conclusions and policy recommendations

This study examines the effects of six determinant variables (namely renewable energy supply, development of environmental patents, economic growth, exports, foreign direct investment and domestic credit to the private sector) on the CO_2 emissions per capita from 2000 to 2013 for the BRIICS countries. In order to gauge the potential heterogeneous effect between carbon emissions and its determinant factors, fixed-effect panel quantile regression method is applied in this study.

The regression results clearly show that the effects of different decisive factors are heterogeneous across the quantiles. The main findings are shown in Fig. 4. Possible explanations about the relationship between the six variables and carbon emission per capita are also presented in Fig.4.



Note: the impacts of the six factors are heterogenous across different quantiles.

Fig. 4. Relationships between RES, DET, GDP, EXP, FDI, DCP and CEPC.

Compared with the extant studies about the CO_2 emissions of developed countries, some of the conclusions are similar. Renewable energy can reduce CO_2 emissions. Baek (2016) and Cheng et al. (2018) demonstrated that renewable energy can significantly reduce CO_2 emissions in USA and EU 28 countries, respectively. However, some of the conclusions in this paper are inconsistent with studies on developed countries: (1) Innovation is crucial to the reduction of CO2 emissions in 28 OECD countries (Mensah et al., 2018). The result is contrary to our conclusions about the environmental patents. (2) GDP has negative impacts on CO_2 emissions in EU 28 countries (Cheng et al., 2018). The result is not consistent with the conclusions about GDP.

Compared with traditional mean regression methods, the fixed-effect panel quantile method allows us to gauge the heterogenous impacts of RES, DET, GDP, EXP, FDI and DCP on CEPC. Specifically, (1) Renewable energy supply reduces carbon emissions per capita, with the strongest effect in the 95th quantile. (2) Development of environmental patents accelerate carbon emissions per capita, but only significantly affects the CO_2 emissions per capita at the upper tail of the conditional distribution. (3) GDP per capita enhances CO_2 emissions per capita, with the strongest effect in the 5th quantile. (4) Exports increase carbon emissions per capita with an asymmetric inverted U-sharped impact. (5) Foreign direct investment declines carbon emissions per capita, but only significantly influences the carbon emissions per capita at the medium and upper of the conditional distribution. (6) Domestic credit to private sectors raises carbon emissions per capita with gradually decreasing impacts along with all the quantiles.

Based on the findings above, we propose the following policy recommendations: (1) development of renewable energy. Although the process of industrialization needs plenty of natural resources, especially energy, the BRIICS countries can accelerate the development of renewable energy. The development of renewable energy can not only satisfy the energy need of the industrialization, but also mitigate carbon emissions. (2) Promulgation of environmental regulations. The BRIICS countries should promulgate environmental regulations to break down the obstacles which prohibit patents from fully applied in the secondary sectors. Moreover, the BRIICS countries should issue other policies which can stimulate the invention of environmental-related patents and accelerate the diffusion of these patents. (3) Adjustment of economic structure. The BRIICS countries should continue their transition from extensive economies to intensive economies. The BRIICS countries have realized that they should adjust their economic structure towards energy-intensive industry and service and promote the development of high technology. This strategy can not only maintain the development of their economies, but also change their roles in the global supply chain. Moreover, it can reduce carbon emissions. (4) Foreign capital inducement. The BRIICS countries should continue to introduce environmentally-friendly foreign investment and high technologies which are related to carbon reduction, such as carbon capture and storage.

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Appendix A

Appendix A. Description of variables.

Abbreviation	Variable name	Units
CEPC	CO_2 emissions per capita	kg/person
RES	Renewable energy supply	% (of total primary energy supply)
DET	Development of environment-related technologies	items /person
GDP	GDP per capita	2010 USD/person

EXP	Exports of goods and services	% (of GDP)
FDI	Foreign direct investment	2010 USD/person
DCP	Domestic credit to private sector	% (of GDP)

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