

1 Heterogeneous impacts of renewable energy and 2 environmental patents on CO₂ emission - evidence from 3 the BRIICS

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14 **Abstract:** The study explores the impacts of renewable energy, environmental patents, economic growth
15 and other variables on the CO₂ emission per capita from 2000 to 2013 for the BRIICS countries. Using
16 both the panel OLS methods and panel quantile regression method, we find that the effects of the
17 determinant variables are heterogeneous across quantiles. Specifically, renewable energy supply reduces
18 CO₂ emissions per capita, with the strongest effect at the 95th quantile. Development of environmental
19 patents accelerates carbon emissions per capita, but only significantly affects the CO₂ emissions per capita
20 at the upper tail of the conditional distribution. GDP per capita enhances CO₂ emissions per capita, with
21 the most substantial effect in the 5th quantile. Exports increase carbon emissions per capita with an
22 asymmetric inverted U-shaped impact. Foreign direct investment reduces carbon emissions per capita,
23 but only significantly influences the carbon emissions per capita at the medium and upper of the
24 conditional distribution. Domestic credit to private sectors raises carbon emissions per capita with
25 gradually decreasing impacts along all quantiles. We propose several policy recommendations based on
26 the results.

27
28 **Keywords:** BRIICS; CO₂ emissions; environmental patent; panel quantile regression; renewable energy

30 1. Introduction

31 Brazil, Russia Federation, India, Indonesia, China and South Africa, six of very promising emerging
32 national economies, constitute the BRIICS¹. The BRIICS not only have significant impacts on global
33 affairs due to their rapid economic growth, huge population, and large foreign reserves (Chang, 2015;
34 Wang et al., 2016a; Zaman et al., 2016), but also play a crucial role in the global carbon emissions
35 mitigation (Azevedo et al., 2018; Dong et al., 2017; Nassani et al., 2017). According to the statistics of
36 British Petroleum (BP), the carbon dioxide (CO₂) emissions of the BRIICS members reached 14,110
37 million tonnes (Mt) in 2013, which was about two times compared with the CO₂ emissions of the BRIICS
38 members in 2000 (see Fig.1). Moreover, the BRIICS members have emitted over 40% of world carbon
39 emissions every year since 2009 (BP, 2018).

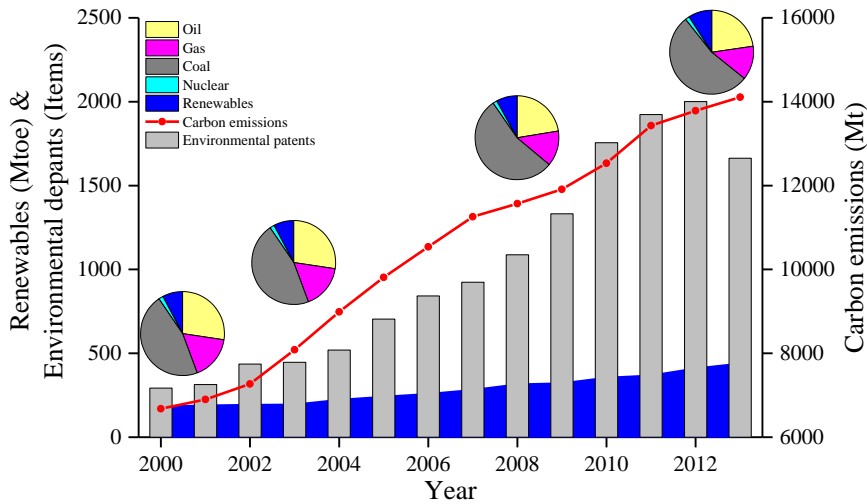
40 The substantial carbon emissions have posed a tremendous environmental challenge for the BRIICS
41 (Azevedo et al., 2018; Sebri and Ben-Salha, 2014; Shahbaz et al., 2016). So far the BRIICS have mainly
42 attempted to mitigate environmental degradation from two aspects: (1) to accelerate the development of
43 renewable energy. Renewable energies are cleaner than traditional fossil energies because they emit fewer
44 greenhouse gas from the perspective of the life cycle assessment (Asdrubali et al., 2015; Odeh and
45 Cockerill, 2008). As shown in Fig.1, the renewables energies' consumption in BRIICS kept increasing, as
46 it raised from 180.7 million tonnes of oil equivalent (Mtoe) in 2000 to 437.3 Mtoe in 2013 with an annual
47 growth rate of approximate 7.03%. Besides, the percentage of renewables in energy consumption mix of
48 the BRIICS also kept increasing (see Fig.1). (2) to advance efficiency-enhancing technologies.
49 Technological innovation, especially environmental-related patents can enhance energy efficiency, thus
50 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, CO₂ emissions per capita; Choi, Choi's modified P Unit-Root; CO₂, 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.

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

56



57 **Fig. 1.** BRIICS's carbon emissions, energy consumption mix and environmental patents from 2000-2013.
 58 *Note: Data are obtained from BP (2018) and the OECD Environment database.*
 59

60

61 Although the renewable energy consumption and the quantity of environmental patents have
 62 increased during the past year in the BRIICS, the CO₂ emissions of the BRIICS countries still raise.
 63 Therefore, an investigation, which explores the impacts of renewable energy and environmental patents
 64 on carbon emissions, should be conducted to help the BRIICS association to enact climate change policies.
 65 Moreover, the traditional panel regression methods applied in the previous literature are usually based on
 66 conditional mean methods. Unlike them, we apply the fixed-effect panel quantile regression method
 67 proposed by Koenker (2004). As far as we know, no empirical studies have applied the fixed-effect panel
 68 quantile regression method to study the carbon emissions issues in the BRIICS countries. Given these
 69 motivations, this study investigates the impacts of renewable energy and environmental patents on carbon
 70 emission of the BRIICS association by using the annual data from 2000 to 2013².

71 This study contributes to the related literature from two aspects: Firstly, it applies the fixed-effect
 72 panel quantile regression method to investigate the impacts of renewable energy supply, environmental
 73 patents and other control variables on CO₂ emissions in the BRIICS countries. By applying this method,

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

74 the problems caused by the overlook of individual heterogeneity and distributional heterogeneity can be
75 solved; moreover, the different effects of the determinant factors across the CO₂ emissions quantiles can
76 be captured. Secondly, it examines the impacts of environmental patents on CO₂ emissions. When
77 exploring the decisive factors of CO₂ emissions, the existing literature focuses on economic growth, energy
78 consumption, renewable energy consumption, foreign direct investment, natural gas and so on, but
79 previous studies neglect technology. To fill this gap, this paper investigates the impacts of environmental
80 patents on carbon emissions.

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

85 **2. Literature review**

86 *2.1 The carbon emission and its decisive factors*

87 The first proposition about the relationship between carbon emission and its decisive factors is
88 proposed by Kuznets (1955), and the proposition is the Environmental Kuznets Curve (EKC) hypothesis.
89 In the EKC hypothesis, an inverse U-shaped relationship between CO₂ emissions and economic growth
90 (usually depicted by gross domestic production, GDP) was proposed by Kuznets. Later on, several scholars
91 explored the effects of the economic growth on CO₂ emissions and tested the validity of the EKC
92 hypothesis via empirical studies, such as Selden and Song (1994), Holtz-Eakin and Selden (1995) and
93 Dinda and Coondoo (2006).

94 Several other determinant factors may affect carbon emissions. These factors include electricity
95 consumption (Cowan et al., 2014), energy consumption (Antonakakis et al., 2017; Wang et al., 2016b),
96 natural gas consumption (Dong et al., 2018; Li and Su, 2017), renewable energy consumption (Cheng et
97 al., 2018; Gozgor, 2018; Sarkodie and Adams, 2018), nuclear energy consumption (Baek, 2016),
98 agriculture (Jebli and Youssef, 2017; Liu et al., 2017a), foreign direct investment (Sarkodie and Strezov,
99 2019; Zhu et al., 2016), trade openness (Hu et al., 2018; Piaggio et al., 2017), transport service (Nassani
100 et al., 2017), lag of carbon emission (Azevedo et al., 2018), urbanization (Wang et al., 2016a), finance
101 (Nassani et al., 2017) and so on.

102 These studies explored different determinant factors of carbon emissions, and provided related policy
103 recommendations: (1) to promote the development of renewable energy. Wang et al. (2016b) and Dong et
104 al. (2018) suggested that China should develop renewable energy to reduce emissions. Sarkodie and Adams
105 (2018) recommended that South Africa should diversify its energy portfolio by developing renewable
106 energy. (2) to develop sustainable agriculture. Liu et al. (2017a) suggested that the 4 selected ASEAN
107 countries should develop sustainable agriculture in mitigate CO₂ emissions. (3) to promote the
108 development of the service industry. Sarkodie and Adams (2018) and Wang et al. (2016a) proposed that
109 the governments should shift their economies to a service-oriented economy.

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

118 *2.2 The methodologies applied in studies about the carbon emissions and its decisive factors*

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

125 Regarding the carbon emission of the BRICS countries, several scholars applied different
126 econometric methods to explore the impacts of different determinant variables. Azevedo et al. (2018)
127 divided the BRICS countries into two groups and applied the OLS method to investigate the impacts of
128 the lag of carbon emissions. They found that individual heterogeneity existed in the BRICS members.
129 Wang et al. (2016a) applied a panel Granger causality method proposed by Canning and Pedroni (2008)
130 to study the relationship between urbanization and carbon emissions. Cowan et al. (2014) applied bootstrap

131 panel causality methodology to explore the causal effect of electricity consumption on carbon emissions.
132 Dong et al. (2017) employed a VECM to investigate the relationship among CO₂ emissions, renewable
133 energy and natural gas consumptions. Nassani et al. (2017) used panel fixed-effect regression method to
134 examine the impacts of finance, transport, energy and growth factors. Sebri and Ben-Salha (2014) applied
135 the autoregressive distributed lag model and VECM to investigate the causal relationship among economic
136 growth, renewable energy consumption, carbon emissions and trade openness. In summary, previous
137 studies about the BRICS countries usually employed the conditional mean method and did not investigate
138 the impacts of environmental patents on carbon emissions.

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

152 **3. Data and Methodology**

153 *3.1. Data*

154 To investigate the impacts of renewable energy supply, environmental patents and other variables on
155 the CO₂ emissions, we collect data from the World Development Indicators (World Bank, 2018) and the
156 Organization for Economic Cooperation and Development (OECD) Environment Database (OECD, 2018)
157 from 2000 to 2013 for the BRIICS members. The sample size is 84. Appendix A summarized the seven
158 variables used in this study, namely CO₂ emissions per capita (denoted by CEPC), renewable energy

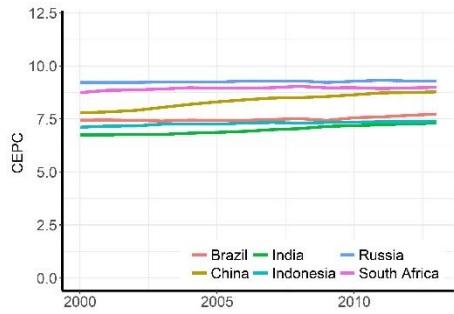
159 supply (denoted by RES), development of environment-related technologies (denoted by DET), GDP per
160 capita (denoted by GDP), exports of goods and services (denoted by EXP), foreign direct investment
161 (denoted by FDI) and domestic credit to private sector (denoted by DCP).

162 CO₂ emissions per capita (CEPC) represents the units of CO₂ emissions from the combustion of
163 primary energy (such as coal, crude oil, natural gas and other fuels) divided by population. Fig. 1a depicts
164 the time series of the CEPC (after logarithm) for the six BRIICS countries. The CEPC of Russia is the
165 highest among the six BRIICS countries, while India produces the lowest CEPC. Fig.1a indicates that the
166 distributions of CEPC in different countries are diverse.

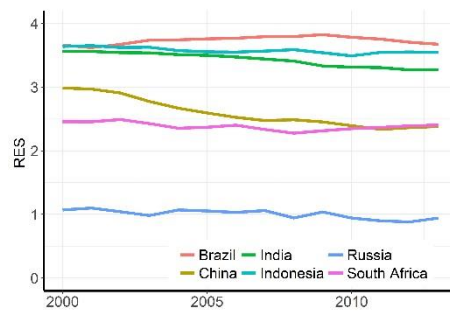
167 Renewable energy supply (RES) is denoted as the ratio of renewable energy supply to the aggregate
168 primary energy supply. Renewable energies include geothermal, solar energy, combustible renewables,
169 wind and so on. Fig. 1b reveals the time series of the RES (after logarithm) for the six BRIICS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

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

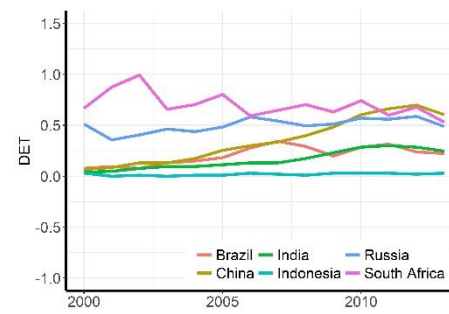
184 GDP per capita (GDP) measures a country's economic wealth of the population of a nation and is
185 expressed at constant 2010 USD PPP prices. GDP per capita also implies the economic growth of a nation.
186 Moreover, economic growth is widely recognized as an essential factor for CO₂ emission in previous
187 research (Kuznets, 1955; Sarkodie and Strezov, 2019; Selden and Song, 1994). Fig. 1d shows the series
188 of the GDP (after logarithm) for the six BRIICS countries. Russia is the wealthiest country, while India is



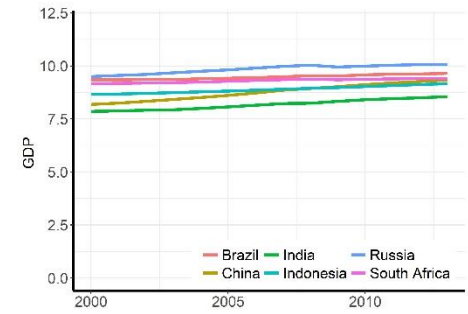
(a) carbon emission per capita



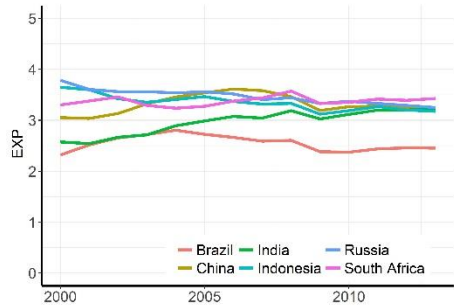
(b) renewable energy supply



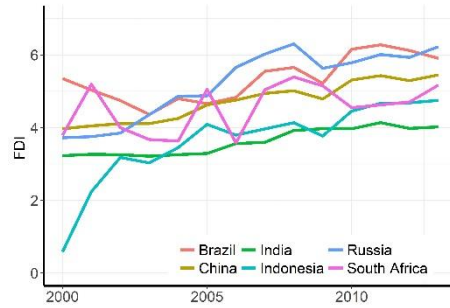
(c) development of environmental patents



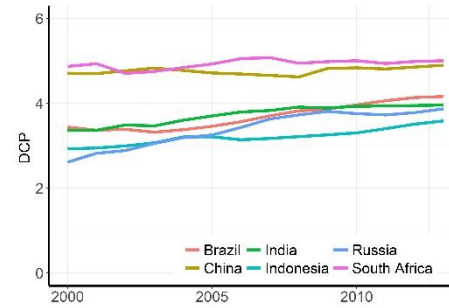
(d) GDP per capita



(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 BRICS countries over 2000–2013 (after logarithm).

192 the poorest county among BRIICS.

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

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

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

213 Before conducting the empirical analysis, all variables are transformed into natural logarithms. Table
214 1 presents a summary of the statistical description for the seven variables, including the minimum value,
215 maximum value, 25th quantile, 75th quantile, mean value, standard deviation, skewness, kurtosis and
216 Jarque–Bera test. The skewness values and the kurtosis values in Table 1 indicate that all the seven
217 variables are not normally distributed. Moreover, the results of Jarque–Bera statistical test also imply that
218 these series depart from normal distributions (except GDP). Overall, the results imply that the OLS method
219 is not suitable for these series, providing supports for the panel quantile regression methods we apply.

220

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

221 3.2. Panel quantile regression

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

227 In general, the conditional mean regression method can provide unbiased results if the error follows
228 the normal distribution. However, the normality assumption is hardly satisfied in empirical studies. As
229 mentioned in Section 3.1, the variables in this study do not conform to the normality assumption. In this
230 case, the conditional mean regression may yield biased coefficients, or fails to provide reliable
231 relationships (Ren et al., 2019; Zhu et al., 2016). Moreover, individual heterogeneity is also neglected in
232 the conditional mean regression method. Therefore, in order to overcome these shortcomings of the
233 conditional mean regression method, the quantile regression method is proposed by Koenker and Bassett
234 (1978), and is adopted by many scholars.

235 The fixed-effects panel quantile model is expressed as:

$$236 Q_{Y_{i,t}}(\tau|X_{i,t}) = \alpha(\tau)'X_{i,t} + \beta_i, \quad i = 1, \dots, N, t = 1, \dots, T \quad (1)$$

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

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

268 **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

269 *4.2. Panel regression results*

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

274 **Table 3.** OLS regression results

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

Figures in parentheses are standard error.

*significant at 10% level

**significant at 5% level

***significant at 1% level

275
276 The relationships between RES and CEPC in the three conditional mean regression models are
277 presented in Table 3. In these three models, RES has a negative impact on carbon emissions: one more
278 unit of RES reduces CEPC by 0.5382, 0.4787 and 0.5967 unit, respectively. The results imply that
279 renewable energy is beneficial for carbon mitigation. This effect is also observed by Nassani et al. (2017)
280 and Dong et al. (2017), who confirm that renewable energy can reduce carbon emissions in BRICS.
281 Moreover, the results also coincide with Liu et al. (2017a), who confirms that renewable energy can reduce
282 carbon emission in Indonesia.

283 The impact of DET on CO₂ emissions is positive in the three conditional mean regression models
284 (see Table 3). Specifically, one more unit of DET increases CEPC by 0.1712 unit in the pooled OLS model,
285 but the impact is not significant. However, in the OLS one-way fixed-effect model and OLS two-way
286 fixed model, one more unit of DET significantly increases CEPC by 0.129 and 0.2638 unit, respectively.
287 Thus, we find an increasing effect of DET on the CEPC in the three conditional mean regression model,
288 indicating that the development of environmental patents increases carbon emissions in the BRIICS
289 countries.

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

294 With regards to FDI and DCP, the results of the three conditional mean regression method are mixed.
295 To be specific, a significant negative effect of FDI on the CO₂ emissions is observed in the pooled OLS
296 model, while an insignificant positive impact of FDI on the carbon emissions is presented in the OLS one-
297 way and two-way fixed-effect model. As for DCP, a significant positive impact is evidenced in the pooled
298 OLS model, while a significant negative impact is provided in the OLS one-way and two-way fixed-effect
299 model. One possible explanation for the inconsistent results is that the OLS method neglects the individual
300 heterogeneity and distributional heterogeneity in the panel data (Cheng et al., 2018; Zhu et al., 2016).
301 Therefore, the panel quantile regression method should be used to provide a more explicit relationship
302 between carbon emissions and the decisive factors.

303 *4.3. Panel quantile regression results*

304 In this subsection, we use the panel quantile regression method to reflect the limitation of the
305 conditional mean regression method. The heterogeneous impacts of RES, DET, GDP, EXP, FDI and DCP
306 on the CEPC are estimated with the fixed-effect panel quantile regression method and presented in Table
307 4 and Fig. 3. The results are reported for the 5th, 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th and
308 95th percentiles of the conditional carbon dioxide emission per capita. The regression results in Table 4
309 and Fig. 3 reveal that the impacts of various factors on CEPC are heterogeneous.

310 The impact of renewable energy supply on carbon dioxide emission per capita is heterogeneous and
311 significant at 1% level. The ln(RES) row of Table 4 demonstrates that RES decreases CEPC in all quantiles,
312 but the impacts of RES on CEPC are asymmetric through different quantiles. To be specific, the
313 coefficients of RES have a decreasing trend in different quantiles, from -0.419 in the 10th quantile to -
314 0.601 in the 95th quantile. In other words, the mitigation impacts of RES on CEPC increase across the
315 quantiles. The aggregate effect⁴ of RES on CPEC is consistent with the conditional mean regression
316 results in Table 3.

317 The impact of the development of environmental patents on CO₂ emission per capita is heterogeneous.
318 In the ln(DET) row of Table 4, CEPC increases with a promotion in the development of environmental
319 patents. Moreover, the impacts of DET on CEPC have an increasing trend. The coefficients of ln(DET)
320 increase from 0.0284 in the 5th quantile to 0.3395 in the 80th quantile, then decrease slightly, and reduce
321 to 0.2518 in the 95th quantile. However, only the coefficient in the 95th quantile is significant. The
322 aggregate weight of DET on CEPC agrees with the conditional mean regression results in Table 3.

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

328 The effect of exports on carbon emissions per capita is heterogeneous. The ln(EXP) row in Table 4
329 implies that CEPC asymmetrically increases with increasing exports across all quantiles. Specifically, the
330 impacts are the strongest at the lower quantiles, which was about 0.39, then the impacts decrease from
331 0.3964 in the 30th quantile to 0.1587 in the 70th quantile, and becomes stable in the upper tail of the

⁴ Aggregate effect (weight) denotes the aggregate impacts of the decisive factors across different CO₂ quantiles.

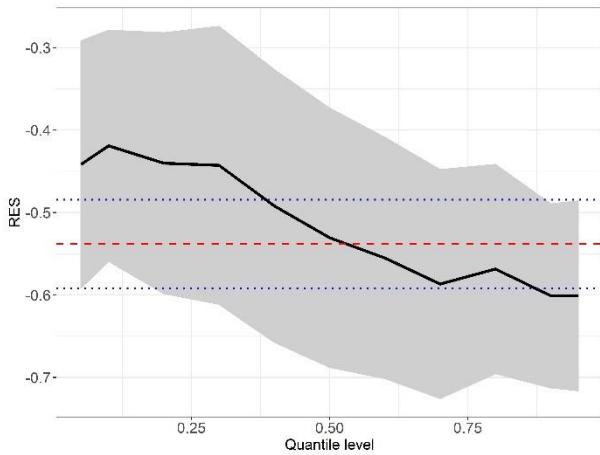
332 conditional CEPC distribution. Moreover, the coefficients are significant for all quantiles except for 5th
333 and 70th quantiles. The aggregate weight of EXP on CEPC agrees with the regression results in Table 3.

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

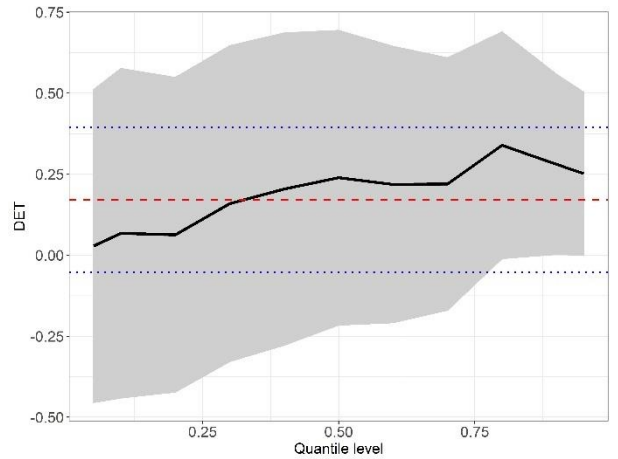
341 The impact of domestic financial development on CO₂ emissions per capita is heterogeneous and
342 significant at 1% level. The ln(DCP) row in Table 4 shows that CEPC increases with increasing domestic
343 credit to the private sector, but the impacts have a declining trend. Specifically, the coefficients decrease
344 from 0.5346 in the 5th quantile to 0.3471 in the 95th quantile. The aggregate weight of DCP on CEPC is
345 consistent with the results of OLS regression in Table 3.

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

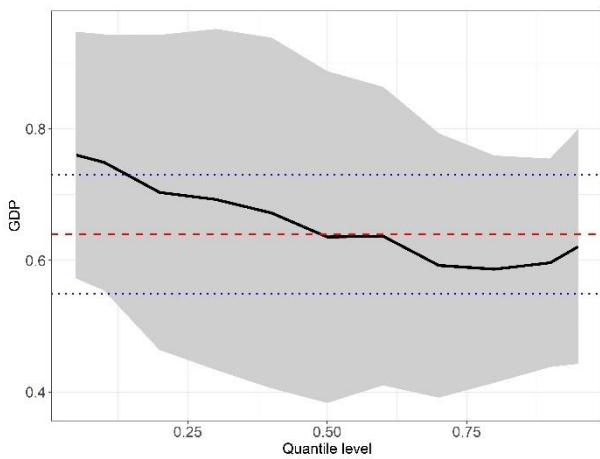
356 We proceed with a robustness check to further test the validity of the regression results. The
357 robustness check mainly considers different values for μ . To be specific, we conduct the panel quantile
358 regression by using different μ , namely 0.1, 0.9 and 2.0. The results are presented in Table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



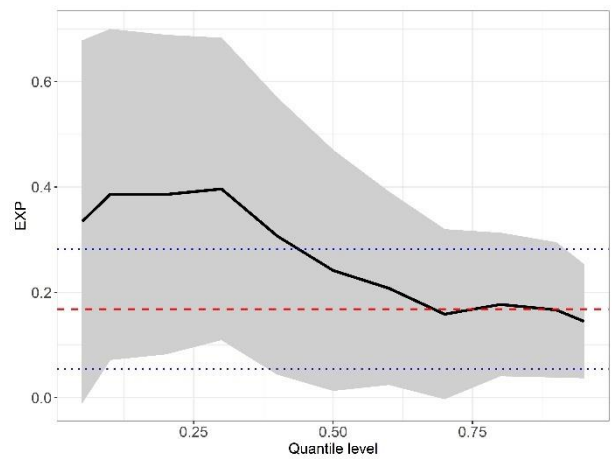
(a) *RES*



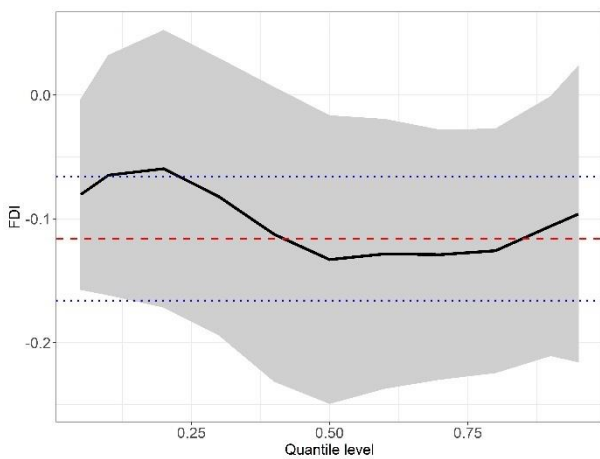
(b) *DET*



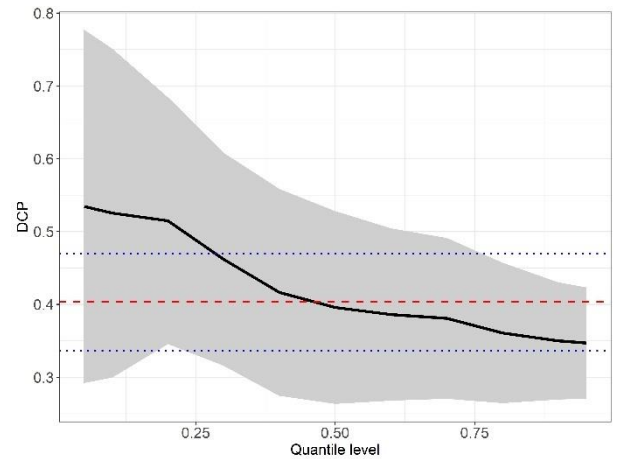
(c) *GDP*



(d) *EXP*



(e) *FDI*



(f) *DCP*

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364
365

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 (-0.3442)	-0.7001 (-0.4818)	-0.1690 (-0.1177)	0.2270 (0.1673)	1.1885 (0.9139)	2.0278 (1.7609)	2.2388*** (2.2010)	2.9352*** (3.1136)	2.9294*** (3.4353)	2.9701*** (3.6308)	2.8134*** (3.1453)
ln(RES)	-0.4417*** (-5.7749)	-0.4190*** (-5.8596)	-0.4401*** (-5.4527)	-0.4427*** (-5.1478)	-0.4920*** (-5.8316)	-0.5305*** (-6.6135)	-0.5551*** (-7.4367)	-0.5867*** (-8.2871)	-0.5685*** (-8.7747)	-0.6009*** (-10.5518)	-0.6010*** (-10.2368)
ln(DET)	0.0284 (0.1154)	0.0678 (0.2612)	0.0631 (0.2546)	0.1593 (0.6403)	0.2042 (0.8304)	0.2393 (1.0312)	0.2183 (1.0034)	0.2199 (1.1058)	0.3395 (1.9015)	0.2808* (1.9799)	0.2518* (1.9604)
ln(GDP)	0.7600*** (7.9756)	0.7489*** (7.5731)	0.7031*** (5.7719)	0.6927*** (5.2564)	0.6721*** (4.9596)	0.6355*** (4.9570)	0.6369*** (5.5207)	0.5922*** (5.8033)	0.5866*** (6.6935)	0.5963*** (7.4132)	0.6208*** (6.8680)
ln(EXP)	0.3343 (1.9097)	0.3858* (2.4131)	0.3856** (2.4995)	0.3964** (2.7154)	0.3068* (2.2951)	0.2417* (2.0785)	0.2078* (2.2311)	0.1587 (1.9374)	0.1770** (2.5645)	0.1668** (2.5636)	0.1449** (2.6523)
ln(FDI)	-0.0804* (-2.0532)	-0.0647 (-1.3131)	-0.0596 (-1.0450)	-0.0822 (-1.4440)	-0.1126 (-1.8606)	-0.1329* (-2.2425)	-0.1283* (-2.3167)	-0.1289** (-2.5133)	-0.1258** (-2.5080)	-0.1059* (-1.9856)	-0.0961 (-1.5786)
ln(DCP)	0.5346*** (4.3342)	0.5254*** (4.5772)	0.5149*** (5.9860)	0.4619*** (6.2217)	0.4165*** (5.7807)	0.3958*** (5.8924)	0.3862*** (6.4363)	0.3809*** (6.8034)	0.3608*** (7.3925)	0.3499*** (8.6033)	0.3471*** (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
$\mu = 0.1$	ln(RES)	-0.4396 (0.0022)	-0.4214 (0.0022)	-0.4392 (0.0023)	-0.4397 (0.0024)	-0.4971 (0.0010)	-0.5347 (0.0004)	-0.5526 (0.0002)	-0.5842 (0.0001)	-0.5673 (0.0001)	-0.5991 (0.0000)	-0.5968 (0.0000)
	ln(GDP)	0.7636 (0.0003)	0.7489 (0.0005)	0.7045 (0.0014)	0.6830 (0.0024)	0.6823 (0.0023)	0.6412 (0.0026)	0.6270 (0.0016)	0.5854 (0.0010)	0.5877 (0.0008)	0.5939 (0.0006)	0.6207 (0.0005)
	ln(EXP)	0.3468 (0.1460)	0.3896 (0.1101)	0.3939 (0.1063)	0.4137 (0.0663)	0.2998 (0.1315)	0.2386 (0.1689)	0.2186 (0.1410)	0.1659 (0.1225)	0.1785 (0.0456)	0.1726 (0.0378)	0.1509 (0.0413)
$\mu = 0.9$	ln(RES)	-0.4417 (0.0020)	-0.4190 (0.0023)	-0.4401 (0.0029)	-0.4427 (0.0030)	-0.4920 (0.0018)	-0.5305 (0.0007)	-0.5551 (0.0004)	-0.5867 (0.0002)	-0.5685 (0.0001)	-0.6009 (0.0001)	-0.6010 (0.0001)
	ln(GDP)	0.7600 (0.0002)	0.7489 (0.0002)	0.7031 (0.0011)	0.6927 (0.0020)	0.6721 (0.0023)	0.6355 (0.0024)	0.6369 (0.0013)	0.5922 (0.0008)	0.5866 (0.0006)	0.5963 (0.0005)	0.6208 (0.0002)
	ln(EXP)	0.3343 (0.1262)	0.3858 (0.0824)	0.3856 (0.0866)	0.3964 (0.0584)	0.3069 (0.1001)	0.2417 (0.1173)	0.2078 (0.0951)	0.1587 (0.1223)	0.1770 (0.0616)	0.1668 (0.0375)	0.1449 (0.0607)
$\mu = 2$	ln(RES)	-0.4427 (0.0012)	-0.4179 (0.0013)	-0.4405 (0.0017)	-0.4443 (0.0020)	-0.4896 (0.0009)	-0.5286 (0.0004)	-0.5572 (0.0002)	-0.5853 (0.0001)	-0.5690 (0.0001)	-0.6018 (0.0000)	-0.6030 (0.0000)
	ln(GDP)	0.7583 (0.0003)	0.7489 (0.0004)	0.7025 (0.0014)	0.7017 (0.0015)	0.6674 (0.0020)	0.6309 (0.0019)	0.6444 (0.0009)	0.5929 (0.0005)	0.5861 (0.0004)	0.5974 (0.0004)	0.6208 (0.0004)
	ln(EXP)	0.3285 (0.1282)	0.3840 (0.0832)	0.3818 (0.0985)	0.3822 (0.0739)	0.3101 (0.1004)	0.2447 (0.1245)	0.1983 (0.1357)	0.1608 (0.1134)	0.1763 (0.0545)	0.1641 (0.0392)	0.1421 (0.0452)

Note: Numbers in the parentheses represent p-value.

372

373 **5. Discussion**

374 *5.1. The analysis of renewable energy supply and carbon emissions per capita*

375 All regression results reveal that renewable energy supply has a negative impact on carbon
376 emissions per capita. This result is consistent with Dong et al. (2017) and Nassani et al. (2017), who
377 find that renewable energy consumption is negatively related to CO₂ emissions. Moreover, this
378 finding is also similar to Hu et al. (2018) who find that increasing share of renewable energy
379 contributes to carbon emission reduction in 25 developing countries, which includes the BIIRCS
380 countries. The life cycle CO₂ emissions of renewable energy are much fewer than the counterpart
381 of fossil energy (Dong et al., 2017). Moreover, all BRIICS countries are promoting the development
382 of renewable energy. Specifically, the renewable energy production in the BRIICS countries had
383 increased from 19.72 terawatt-hours (TWh) in 2000 to 300.67 TWh, with an average annual growth
384 rate of approximate 23.31%. The rapid development of renewable energy strengthens the reduction
385 effect of renewable energy on carbon emissions. Due to these two reasons, the expansion of
386 renewable energy can greatly reduce the carbon emissions in the BRIICS countries.

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

401 energy industry, the economies of scale may even enlarge the difference of renewable energy'
402 negative impacts.

403 *5.2. The analysis of environmental patents and carbon emissions per capita*

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

420 *5.3. The analysis of economic growth and carbon emissions per capita*

421 All the regression results indicate that GDP per capita has a positive impact on carbon
422 emissions per capita. The results are similar to the results of Dong et al. (2017), Hu et al. (2018) and
423 Sarkodie and Strezov (2019), but contrary to the results of Liu et al. (2017b). The positive impacts
424 imply that a raise in GDP per capita will lead to more CEPC. The results can be explained by EKC.
425 According to the EKC hypothesis, economic growth enhances carbon emissions during the
426 industrialization process of an economy. Specifically, industrialization needs massive natural
427 resources, especially energy. Excessive consumption of natural resources could cause the ecological

428 deficit and serious environmental problems (Sarkodie and Strezov, 2019). While as the economy
429 continues to grow, the country will experience a period of post-industrialization. In the post-
430 industrial period, environmental protection awareness, laws and regulations and economic structure
431 towards the tertiary sector could result in a reduction in carbon emissions.

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

440 *5.4. The analysis of exports and carbon emissions per capita*

441 All the regression results reveal that exports have a positive impact on carbon emission per
442 capita in the BRIICS countries. Our results are contrary to that of Hu et al. (2018), who found a
443 negative impact of EXP on carbon emissions for 25 developing countries. The possible explanation
444 is that the BRIICS countries are still located at the low position at the global production chain due
445 to the lack of sophisticated technology and elaborate design, thus they only manufacture or assemble
446 products which are designed by other countries (like China, Indonesia and India), or export natural
447 resources (like Russia and South Africa). During the manufacture process of industrial products and
448 the exploration process of natural resources, CO₂ is emitted in the BRIICS countries, while the
449 produced products or natural resources are used by the importers (this issue is called the embodied
450 carbon dioxide emission) (Chen and Chen, 2011; Meng et al., 2018). This kind of export would
451 cause serious damage to the environment of the BRIICS countries. Therefore, an increase in EXP
452 in the BRIICS countries would lead to more carbon emissions.

453 *5.5. The analysis of foreign direct investment and carbon emissions per capita*

454 The regression results indicate that foreign direct investment (FDI) has a negative impact on

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

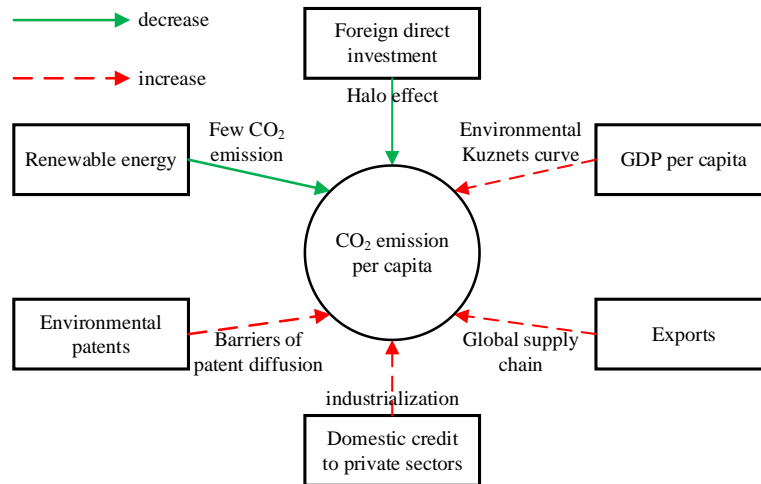
466 *5.6. The analysis of domestic credit to the private sector and carbon emissions per capita*

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

476 **6. Conclusions and policy recommendations**

477 This study examines the effects of six determinant variables (namely renewable energy supply,
478 development of environmental patents, economic growth, exports, foreign direct investment and
479 domestic credit to the private sector) on the CO₂ emissions per capita from 2000 to 2013 for the
480 BRIICS countries. In order to gauge the potential heterogeneous effect between carbon emissions
481 and its determinant factors, fixed-effect panel quantile regression method is applied in this study.

482 The regression results clearly show that the effects of different decisive factors are heterogeneous
 483 across the quantiles. The main findings are shown in Fig. 4. Possible explanations about the
 484 relationship between the six variables and carbon emission per capita are also presented in Fig.4.
 485



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

486
487

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

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

496 Compared with traditional mean regression methods, the fixed-effect panel quantile method
 497 allows us to gauge the heterogenous impacts of RES, DET, GDP, EXP, FDI and DCP on CEPC.
 498 Specifically, (1) Renewable energy supply reduces carbon emissions per capita, with the strongest
 499 effect in the 95th quantile. (2) Development of environmental patents accelerate carbon emissions
 500 per capita, but only significantly affects the CO₂ emissions per capita at the upper tail of the
 501 conditional distribution. (3) GDP per capita enhances CO₂ emissions per capita, with the strongest
 502 effect in the 5th quantile. (4) Exports increase carbon emissions per capita with an asymmetric
 503 inverted U-shaped impact. (5) Foreign direct investment declines carbon emissions per capita, but

504 only significantly influences the carbon emissions per capita at the medium and upper of the
 505 conditional distribution. (6) Domestic credit to private sectors raises carbon emissions per capita
 506 with gradually decreasing impacts along with all the quantiles.

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

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 526 Shanxi Key Subjects Construction (FSKSC).

527 Appendix A

528 **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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