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

**Cheng Cheng [1], Xiaohang Ren [2,\*], Zhen Wang [3], Cheng Yan [4]**

[1] School of Management Science & Engineering, Shanxi University of Finance & Economics, 696 Wucheng Road, Xiaodian, Taiyuan, Shanxi Province 030006, China

[2] School of Mathematical Sciences, University of Southampton, Southampton SO17 1BJ, UK

[3] Academy of Chinese Energy Strategy, China University of Petroleum, 18 Fuxue Road, Changping, Beijing 102249, China

[4] Essex Business School, Colchester, CO4 3SQ, UK

\* Correspondence: domrxh@outlook.com

**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.
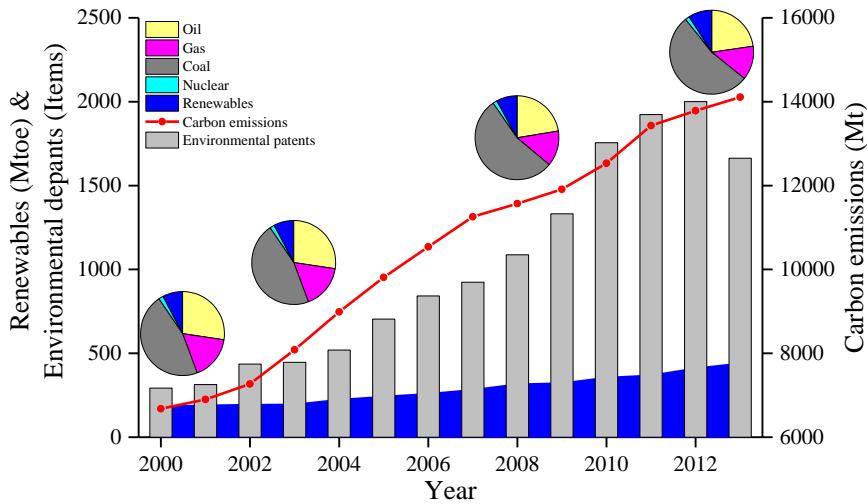


**Fig. 1.** BRIICS's carbon emissions, energy consumption mix and environmental patents from 2000-2013.
*Note: Data are obtained from BP (2018) and the OECD Environment database.*

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.

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 $CO_2$ 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

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

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    $CO_2$ emissions per capita (CEPC) represents the units of $CO_2$ 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 Cloodt, 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 $CO_2$ 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
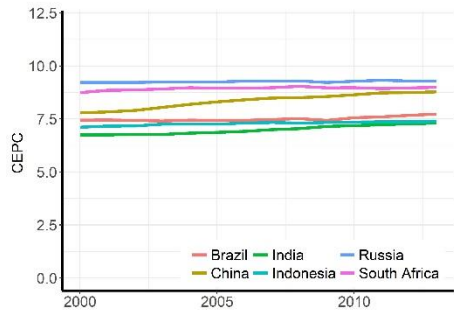
(a) carbon emission per capita
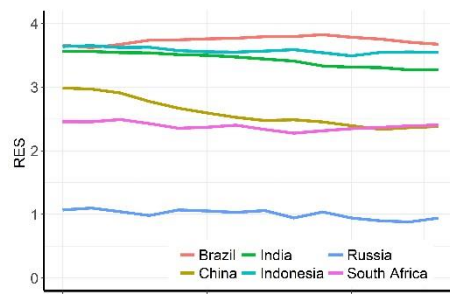
(b) renewable energy supply
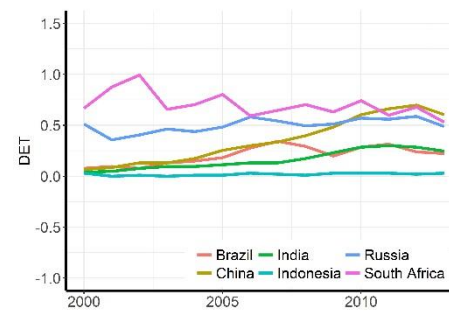
(c) development of environmental patents

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

192    the poorest county among BRIICS.
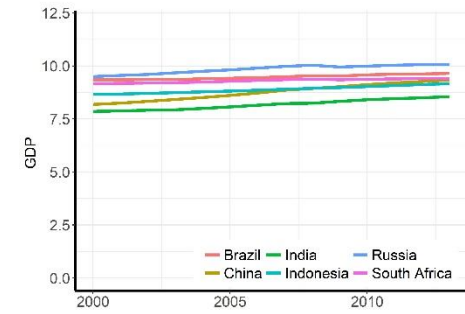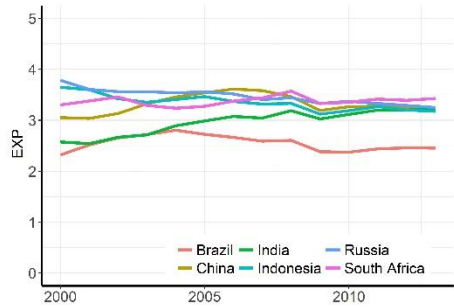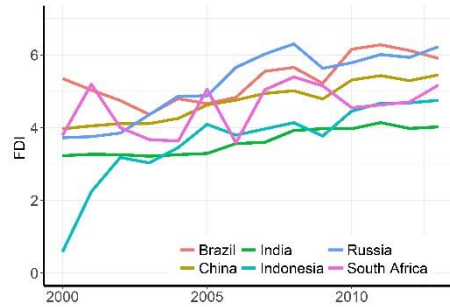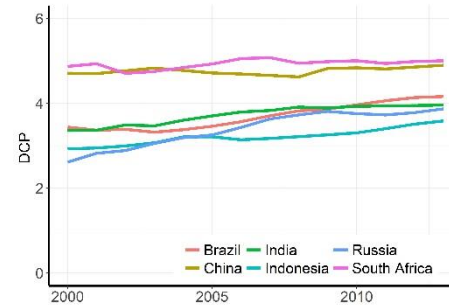
193        Exports of goods and services (EXP) denotes the total value of all goods and services which are sold

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

### 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:

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

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, $\beta_i$ represents the unobserved individual effects. $i$ denotes the BRIICS countries, $t$ denotes the year. Specifically, the model in this paper is:

10

241 $$Q_{Y_{i,t}}(\tau|X_{i,t}) = \alpha_{1,\tau}\text{RES}_{i,t} + \alpha_{2,\tau}\text{DET}_{i,t} + \alpha_{3,\tau}\text{GDP}_{i,t} + \alpha_{4,\tau}\text{EXP}_{i,t} + \alpha_{5,\tau}\text{FDI}_{i,t} + \alpha_{6,\tau}\text{DCP}_{i,t} + \beta_i,$$

242 $$i = 1, \dots, N, t = 1, \dots, T \quad (2)$$

243     The main problem about estimating model (2) is that traditional linear approaches are unfeasible in

244 the quantile regression model. To address such problems, Koenker (2004) introduced a penalty term in the

245 minimization process, which can eliminate unobserved fixed-effects[3]. Compared with other methods, this

246 method has two advantages: (1) it can control the variability caused by a lot of estimated individual

247 coefficients; (2) it can effectively reduce the number of estimated parameters. Following Koenker, we

248 estimate Equation (2) by using the specific model as follows:

249 $$\underset{\alpha}{\arg\min} \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{t=1}^{T} w_k \rho_{\tau_k}\{Y_{i,t} - \alpha_{1,\tau}\text{RES}_{i,t} - \alpha_{2,\tau}\text{DET}_{i,t} - \alpha_{3,\tau}\text{GDP}_{i,t} - \alpha_{4,\tau}\text{EXP}_{i,t} - \alpha_{5,\tau}\text{FDI}_{i,t}$$

250 $$- \alpha_{6,\tau}\text{DCP}_{i,t} - \beta_i\} + \mu \sum_{i=1}^{N}|\beta_i|$$

251 $$i = 1, \dots, N, t = 1, \dots, T \quad (3)$$

252 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. $Y_{i,t}$

253 denotes the carbon dioxide emission per capita in country $i$ at time $t$. $K$ is the index for quantiles, and $w_k$

254 (which equals to $1/K$) is the weight of $k$-th quantile, controlling the relative importance of different

255 quantiles in this estimation (Alexander et al., 2011; Lamarche, 2011; Zhu et al., 2016). $\mu$ is the tuning

256 parameter to control the individual effects. Like Damette and Delacote (2012) and Zhu et al. (2016), we

257 assume that $\mu$ equals to 1 in this paper.

258 **4. Empirical results and discussion**

259 *4.1. Panel unit root test*

260     Before estimating the coefficients, we use several panel unit root tests to check whether the variables

261 are stationary. To be specific, these tests consist of the Levin-Lin-Chu Unit-Root (denoted as LLC) Test

262 (Levin et al., 2002), Choi's modified P Unit-Root (represented by Choi) Test (Choi, 2001), Maddala-Wu

263 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).

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, these 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*** | 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

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 $CO_2$ 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 $CO_2$ 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 effect[4] 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 $CO_2$ 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 $CO_2$ 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 $\mu$. To be specific, we conduct the panel quantile regression by using different $\mu$, 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 $\mu$ are consistent with the results presented in Table 4. Therefore, the robustness check indicates our results are robust and reliable.
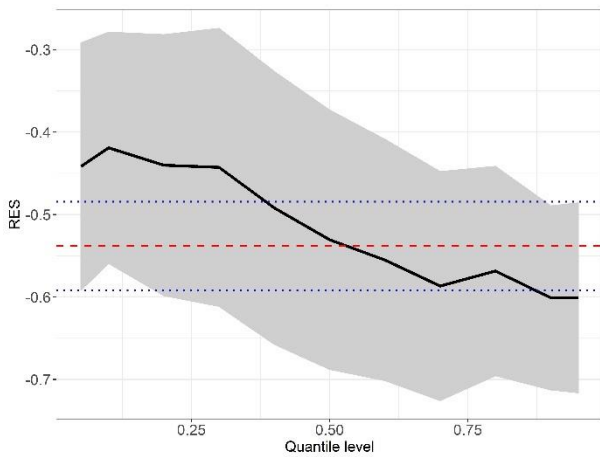
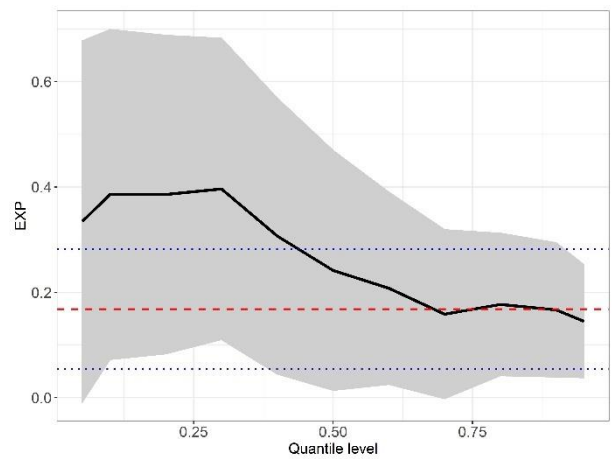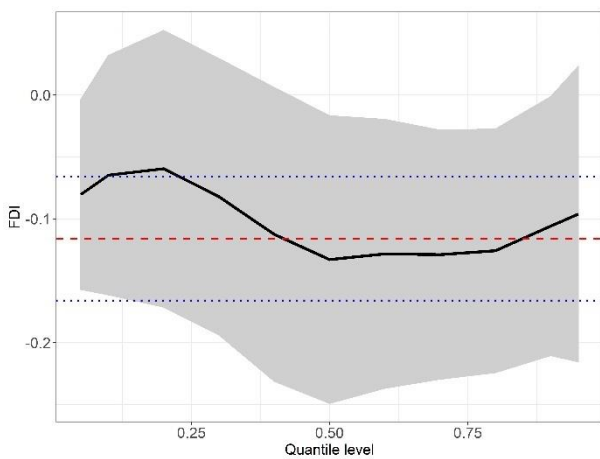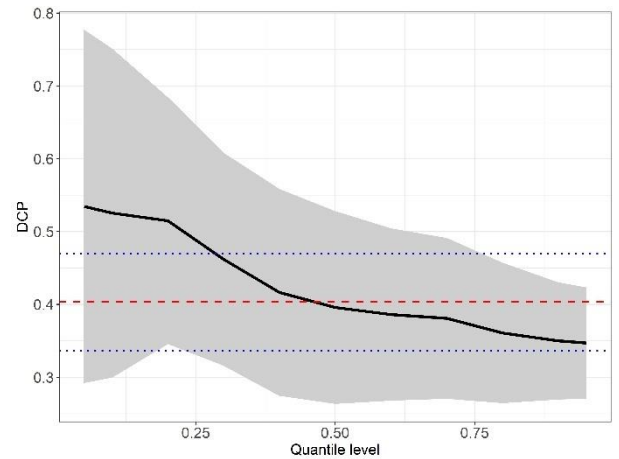(a) *RES*
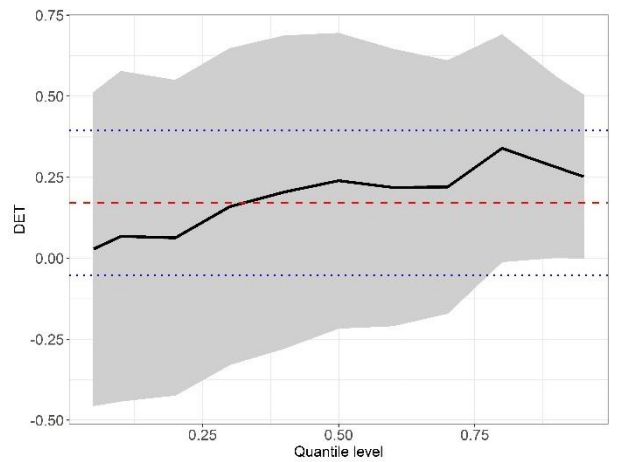
(b) *DET*
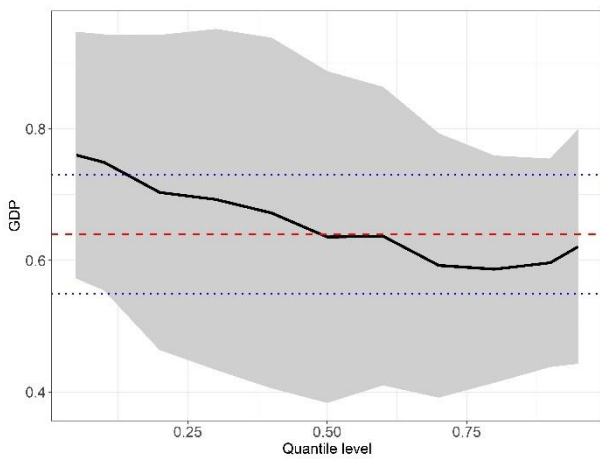
(c) *GDP*

(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).

16

**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

369

370

**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 | -0.4214 | -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) |
| $\mu = 0.9$ | 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) |
| $\mu = 2$ | 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.

371

18

372

**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

401  energy industry, the economies of scale may even enlarge the difference of renewable energy'

402  negative impacts.

*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.

*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, $CO_2$ 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

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.

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
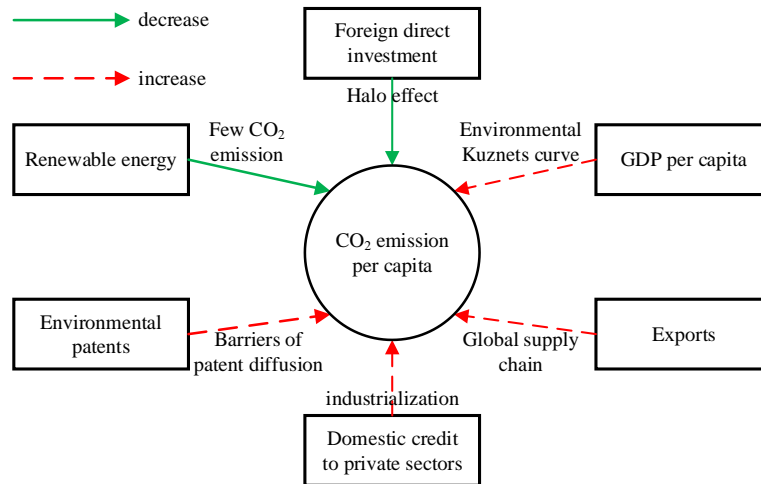


486 Note: the impacts of the six factors are heterogenous across different quantiles.
487 **Fig. 4.** Relationships between RES, DET, GDP, EXP, FDI, DCP and CEPC.

488 Compared with the extant studies about the $CO_2$ emissions of developed countries, some of the

489 conclusions are similar. Renewable energy can reduce $CO_2$ emissions. Baek (2016) and Cheng et

490 al. (2018) demonstrated that renewable energy can significantly reduce $CO_2$ 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 $CO_2$ 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 $CO_2$ emissions per capita at the upper tail of the

501 conditional distribution. (3) GDP per capita enhances $CO_2$ 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-sharped 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.

523 **Acknowledgements**

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 |

24

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

**References**

Alexander, M., Harding, M., Lamarche, C., 2011. Quantile regression for time-series-cross-section data. Int. J. Stat. Manag. Syst. 6, 47-72.

Antonakakis, N., Chatziantoniou, I., Filis, G., 2017. Energy consumption, $CO_2$ emissions, and economic growth: An ethical dilemma. Renew. Sust. Energ. Rev. 68, 808-824.

Asdrubali, F., Baldinelli, G., D'Alessandro, F., Scrucca, F., 2015. Life cycle assessment of electricity production from renewable energies: Review and results harmonization. Renew. Sust. Energ. Rev. 42, 1113-1122.

Atici, C., 2012. Carbon emissions, trade liberalization, and the Japan–ASEAN interaction: A group-wise examination. J. Jpn. Int. Econ. 26, 167-178.

Azevedo, V.G., Sartori, S., Campos, L.M.S., 2018. $CO_2$ emissions: A quantitative analysis among the BRICS nations. Renew. Sust. Energ. Rev. 81, 107-115.

Baek, J., 2016. Do nuclear and renewable energy improve the environment? Empirical evidence from the United States. Ecol. Indic. 66, 352-356.

BP, 2018. BP statistical review of world energy 2018. BP. https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/downloads.html

Canning, D., Pedroni, P., 2008. Infrastructure, long-run economic growth and causality tests for cointegrated panels. The Manchester School 76, 504-527.

Chang, M.C., 2015. Room for improvement in low carbon economies of G7 and BRICS countries based on the analysis of energy efficiency and environmental Kuznets curves. J. Clean. Prod. 99, 140-151.

Chen, Z.M., Chen, G.Q., 2011. Embodied carbon dioxide emission at supra-national scale: A coalition analysis for G7, BRIC, and the rest of the world. Energy Policy 39, 2899-2909.

Cheng, C., Ren, X., Wang, Z., Shi, Y., 2018. The impacts of non-fossil energy, economic growth, energy consumption, and oil price on carbon intensity: Evidence from a panel quantile regression analysis of EU 28. Sustainability 10, 4067.

556       Choi, I., 2001. Unit root tests for panel data. J. Int. Money Finan. 20, 249-272.

557       Cowan, W.N., Chang, T., Inglesi-Lotz, R., Gupta, R., 2014. The nexus of electricity

558       consumption, economic growth and $CO_2$ emissions in the BRICS countries. Energy Policy 66, 359-

559       368.

560       Damette, O., Delacote, P., 2012. On the economic factors of deforestation: What can we learn

561       from quantile analysis? Econ. Model. 29, 2427-2434.

562       Dinda, S., Coondoo, D., 2006. Income and emission: A panel data-based cointegration analysis.

563       Ecol. Econ. 57, 167-181.

564       Dong, K., Sun, R., Dong, X., 2018. $CO_2$ emissions, natural gas and renewables, economic

565       growth: Assessing the evidence from China. Sci. Total Environ. 640-641, 293-302.

566       Dong, K., Sun, R., Hochman, G., 2017. Do natural gas and renewable energy consumption lead

567       to less $CO_2$ emission? Empirical evidence from a panel of BRICS countries. Energy 141, 1466-1478.

568       Gozgor, G., 2018. A new approach to the renewable energy-growth nexus: evidence from the

569       USA. Environ. Sci. Pollut. Res. Int 25, 16590-16600.

570       Guo, L.l., Qu, Y., Tseng, M.-L., 2017. The interaction effects of environmental regulation and

571       technological innovation on regional green growth performance. J. Clean. Prod. 162, 894-902.

572       Hadri, K., 2000. Testing for stationarity in heterogeneous panel data. Econom. J. 3, 148-161.

573       Hagedoorn, J., Cloodt, M., 2003. Measuring innovative performance: is there an advantage in

574       using multiple indicators? Res. Policy 32, 1365-1379.

575       Holtz-Eakin, D., Selden, T.M., 1995. Stoking the fires? $CO_2$ emissions and economic growth.

576       J. Public Econ. 57, 85-101.

577       Hu, H., Xie, N., Fang, D., Zhang, X., 2018. The role of renewable energy consumption and

578       commercial services trade in carbon dioxide reduction: Evidence from 25 developing countries.

579       Appl. Energy 211, 1229-1244.

580       Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econ.

581       115, 53-74.

582       Jebli, M.B., Youssef, S.B., 2017. The role of renewable energy and agriculture in reducing $CO_2$

583       emissions: Evidence for North Africa countries. Ecol. Indic. 74, 295-301.

584       Koenker, R., 2004. Quantile regression for longitudinal data. J. Multivar. Anal. 91, 74-89.

585  Koenker, R., Bassett, G., 1978. Regression Quantiles. Econometrica 46, 33-50.

586  Kuznets, S., 1955. Economic Growth and Income Inequality. Am. Econ. Rev. 45, 1-28.

587  Lamarche, C., 2011. Measuring the incentives to learn in Colombia using new quantile

588 regression approaches. J. Dev. Econ. 96, 278-288.

589  Levin, A., Lin, C.F., Chu, C.S.J., 2002. Unit root tests in panel data: asymptotic and finite-

590 sample properties. J. Econ. 108, 1-24.

591  Li, R., Su, M., 2017. The role of natural gas and renewable energy in curbing carbon emission:

592 Case study of the United States. Sustainability 9, 600.

593  Liu, X., Zhang, S., Bae, J., 2017a. The impact of renewable energy and agriculture on carbon

594 dioxide emissions: Investigating the environmental Kuznets curve in four selected ASEAN

595 countries. J. Clean. Prod. 164.

596  Liu, X., Zhang, S., Bae, J., Liu, X., Zhang, S., Bae, J., 2017b. The nexus of renewable energy-

597 agriculture-environment in BRICS. Appl. Energy 204, 489-496.

598  Maddala, G.S., Wu, S., 1999. A Comparative Study of Unit Root Tests with Panel Data and a

599 New Simple Test. Oxf. Bull. Econ. Stat. 61, 631-652.

600  Meng, J., Mi, Z., Guan, D., Li, J., Tao, S., Li, Y., Feng, K., Liu, J., Liu, Z., Wang, X., Zhang,

601 Q., Davis, S.J., 2018. The rise of South–South trade and its effect on global $CO_2$ emissions. Nat.

602 Commun. 9, 1871.

603  Mensah, C.N., Long, X., Boamah, K.B., Bediako, I.A., Dauda, L., Salman, M., 2018. The effect

604 of innovation on $CO_2$ emissions of OCED countries from 1990 to 2014. Environ. Sci. Pollut. Res.

605 25, 29678-29698.

606  Nassani, A.A., Aldakhil, A.M., Abro, M.M.Q., Zaman, K., 2017. Environmental Kuznets curve

607 among BRICS countries: spot lightening finance, transport, energy and growth factors. J. Clean.

608 Prod. 154, 474-487.

609  Odeh, N.A., Cockerill, T.T., 2008. Life cycle GHG assessment of fossil fuel power plants with

610 carbon capture and storage. Energy Policy 36, 367-380.

611  OECD, 2018. OECD Environment Database. OECD. https://data.oecd.org/environment.htm

612  Piaggio, M., Padilla, E., Román, C., 2017. The long-term relationship between $CO_2$ emissions

613 and economic activity in a small open economy: Uruguay 1882–2010. Energy Econ. 65, 271-282.

Popp, D., 2005. Lessons from patents: Using patents to measure technological change in environmental models. Ecol. Econ. 54, 209-226.

Ren, S., Li, X., Yuan, B., Li, D., Chen, X., 2018. The effects of three types of environmental regulation on eco-efficiency: A cross-region analysis in China. J. Clean. Prod. 173, 245-255.

Ren, X., Lu, Z., Cheng, C., Shi, Y., Shen, J., 2019. On dynamic linkages of the state natural gas markets in the USA: Evidence from an empirical spatio-temporal network quantile analysis. Energy Econ. 80, 234-252.

Sarkodie, S.A., Adams, S., 2018. Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa. Sci. Total Environ. 643, 1590-1601.

Sarkodie, S.A., Strezov, V., 2019. Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. Sci. Total Environ. 646, 862-871.

Sebri, M., Ben-Salha, O., 2014. On the causal dynamics between economic growth, renewable energy consumption, $CO_2$ emissions and trade openness: Fresh evidence from BRICS countries. Renew. Sust. Energ. Rev. 39, 14-23.

Selden, T.M., Song, D., 1994. Environmental Quality and Development: Is There a Kuznets Curve for Air Pollution Emissions? J. Environ. Econ. Manag. 27, 147-162.

Shahbaz, M., Rasool, G., Ahmed, K., Mahalik, M.K., 2016. Considering the effect of biomass energy consumption on economic growth: Fresh evidence from BRICS region. Renew. Sust. Energ. Rev. 60, 1442-1450.

Voigt, S., De Cian, E., Schymura, M., Verdolini, E., 2014. Energy intensity developments in 40 major economies: Structural change or technology improvement? Energy Econ. 41, 47-62.

Wang, Y., Li, L., Kubota, J., Han, R., Zhu, X., Lu, G., 2016a. Does urbanization lead to more carbon emission? Evidence from a panel of BRICS countries. Appl. Energy 168, 375-380.

Wang, S., Zhou, C., Li, G., Feng, K., 2016b. $CO_2$, economic growth, and energy consumption in China's provinces: Investigating the spatiotemporal and econometric characteristics of China's $CO_2$ emissions. Ecol. Indic. 69, 184-195.

Wang, Z., Yang, Z., Zhang, Y., Yin, J., 2012. Energy technology patents–$CO_2$ emissions nexus:

643 An empirical analysis from China. Energy Policy 42, 248-260.

644 World Bank, 2018. World Development Indicators. World Bank.

645 Wurlod, J.-D., Noailly, J., 2018. The impact of green innovation on energy intensity: An

646 empirical analysis for 14 industrial sectors in OECD countries. Energy Econ. 71, 47-61.

647 Zaman, K., Abdullah, A.B., Khan, A., Nasir, M.R.B.M., Hussain, S., 2016. Dynamic linkages

648 among energy consumption, environment, health and wealth in BRICS countries: Green growth key

649 to sustainable development. Renew. Sust. Energ. Rev. 56, 1263-1271.

650 Zhao, X., Yin, H., Zhao, Y., 2015. Impact of environmental regulations on the efficiency and

651 $CO_2$ emissions of power plants in China. Appl. Energy 149, 238-247.

652 Zhu, H., Duan, L., Guo, Y., Yu, K., 2016. The effects of FDI, economic growth and energy

653 consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression. Econ.

654 Model. 58, 237-248.