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The role of renewable energy technological innovation on climate change: Empirical evidence from China

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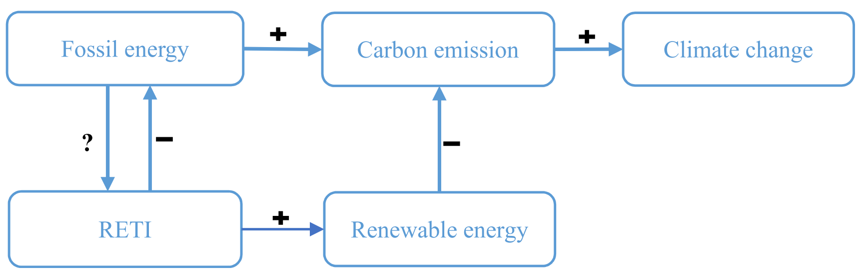
HIGHLIGHTS

- We identify the relationship between renewable energy technological innovation (*RETI*) and CO_2 emissions.
- We find distinct effect of *RETI* on curbing CO_2 under different energy structure.
- The government should pay attention to the role of *RETI*.
- More renewable energy should be encouraged in residential life and production process.

GRAPHICAL ABSTRACT



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ABSTRACT

To develop renewable energy as well as promote China's transition to a low-carbon economy, the government needs to pay attention to renewable energy technological innovation (*RETI*). Using China's provincial panel data from 2000 to 2015, and regarding the CO_2 emissions as the proxy of climate change, this paper identifies the relationship between *RETI* and CO_2 emissions as well as seeks to confirm the role of *RETI* on climate change. The linear regression model confirms that the *RETI* has a significant negative effect on CO_2 emissions. In addition, considering the disparities of energy structure, the impacts of *RETI* on CO_2 emissions may be distinct. We, therefore, construct a panel threshold model by taking into account the distinct effect of *RETI* under different energy structure. We find that the effect of *RETI* on curbing CO_2 emissions decreases with the rising of coal-dominated energy consumption structure but in contrast, this effect increases with the growing proportion of renewable energy generation. This paper provides new insight into the relationship between technological innovation and climate change. Based on these findings, some relevant policy recommendations are proposed.

1. Introduction

The current most concerned environmental problem is climate change and its main cause is considered to be the greenhouse gas emissions (Bekun et al., 2019). The BP statistics showed that the total world fossil energy-related CO_2 emission was 11,190 million tonnes in 1965, but increased to 33,444 million tonnes in 2017, with an average annual growth rate of 3.75%.[1] Climate change will bring potential risks to human activities and life. The frequent occurrences of air pollution and extreme weather conditions have seriously threatened human health and property safety. IPCC's research showed that the impact of climate change would continue for several centuries. If CO_2 emissions are not controlled, the irreversible risks caused by climate change will increase in the future.

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[1] https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/co2-emissions.html.

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As the largest developing country, China's rapid economic growth has consumed a large amount of fossil energy and caused serious environmental problems since the industrialization process. China is currently the largest energy consumer and carbon emitter (Meng et al., 2017; Ma et al., 2019). The large fossil fuel energy consumption has caused high CO_2 emissions. As shown in Fig. 1, the BP statistics show that China's fossil energy-related CO_2 emissions were 9123 million tonnes in 2016, accounting for 27.29% of the world's total. As a responsible developing country, China has always been committed to the work on reducing CO_2 emissions. At the 2015 UN Climate Conference, China promised that the carbon intensity in 2030 would drop by 60%–65% based on 2005 level. In order to successfully accomplish this emissions reduction target, China's emission reduction work will be very arduous in the next decade.

Energy technological innovation is an important way to achieve energy conservation and emission reduction. No matter low-carbon and high-efficiency use of the traditional fossil energy, or the large-scale use of renewable energy at a lower cost, we must rely heavily on technological innovation. For traditional fossil energy, technological innovation can improve energy efficiency and then reduce energy consumption and CO_2 emissions in the production process, finally realize energy saving and emission reduction. For renewable energy, technological innovation can improve the technological level of renewable energy and then promote the development of renewable energy. High renewable energy technological innovation (*RETI*) enables the country to produce renewable energy outputs with a lower cost, in fact, *RETI* level can effectively increase renewable energy supply capacity to meet energy demand as well as change energy structure (Chen and Lei, 2018). Renewable energy is recognized as the future energy because of their free of CO_2 emissions (Sadorsky, 2014), so the large-scale use of renewable energy can improve energy security and mitigate climate change (Irandoust, 2016). Therefore, *RETI* is often considered as a cost-effective way to achieve a low-carbon society (Bayer et al., 2013).

However, the role of *RETI* on CO_2 reduction has not been given sufficient attention. The current literature on CO_2 reduction mainly focuses on the perspectives of the relationship among economic growth, energy consumption, industrialization, and urbanization. And the literature analyzed from the perspective of renewable energy also focuses on the interrelationship between renewable energy development and CO_2 emissions, ignoring the potential role of *RETI*. The CO_2 reduction effect of *RETI* on the society is not only reflected in the rising level of renewable energy power generation, but also in the low-carbon development of production and living. For example, China is now the largest consumer of solar water heater in the world (Liu et al., 2011; Yuan et al., 2013). Also, the biomass energy, which is produced by biomass residue, accounting for 71% of total Chinese rural energy consumption in 2008 (Zhang et al., 2018). In addition, solar buildings and low-carbon cities

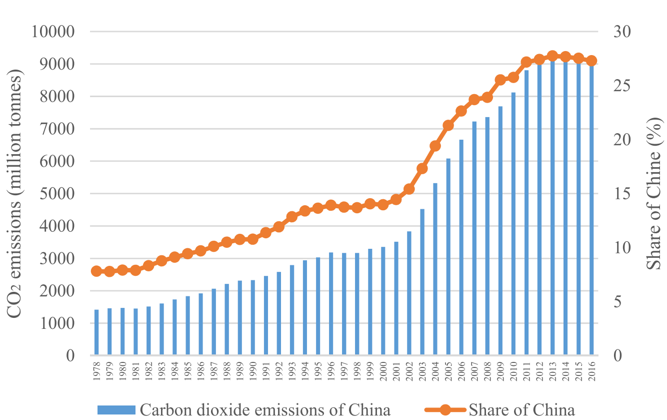

Fig. 1. Fossil fuel CO_2 emissions of China since 1978.
Data sources: BP statistical reviews of world energy 2017.

that are more popular currently are all based on renewable energy. The large-scale and cost-effective use of such renewable energy in society must heavily depend on *RETI*. We argue that *RETI* has no direct effect on CO_2 reduction, but the promotional impact of *RETI* on renewable energy in society can effectively reduce CO_2 emissions. Therefore, *RETI* has an indirect effect on CO_2 emissions. So when analyzing the effect of *RETI*, it is necessary to take into account the influence of the external environment. Because the *RETI* often needs to complete the transformation of achievements to complete a low-carbon social role, but this transformation process often faces many obstacles.

First, compared with traditional fossil energy, the renewable energy industry is a capital-intensive industry and needs lots of funds to be invested in R&D and transformation, resulting in a higher cost of renewable energy than the traditional fossil energy industry (Xu and Lin, 2018). Then, these provinces with coal-dominated energy structure may choose the cheaper coal rather than renewable energy. Meanwhile, compared with the fossil energy, the renewable energy generation is characterized by intermittency and instability (Park and Hur, 2018), which will bring serious risks to the secure and reliable operation of power system. Thus, these provinces may choose fossil energy because it is cheaper and more reliable. Therefore, the coal-dominated energy structure may hinder the transformation of *RETI* achievement, and eventually inhibit the reduction effect of *RETI*. Second, the coal-dominated energy consumption structure will cause an unbalance energy structure, which will hinder the adjustment of energy structure. In the short term, the coal-dominated energy consumption structure is harmful to creating a low-carbon and environmentally friendly social environment, leading to the entire society neglecting the role of renewable energy in low-carbon society, which is not only unfavorable to the progress of *RETI* but also harmful to technological transformation of innovation achievements. However, long-term coal-dominated energy consumption structure emits large amounts of CO_2 emissions and other pollutants, which not only increase the cost of economic growth but also detrimental to the sustainable development of society. Therefore, in the long term, climate change may, in turn, promote the development of *RETI* and eventually promote the development of renewable energy (Xu and Lin, 2018).

Motivated by the above analysis, this paper mainly answers the following questions: (1) Is *RETI* beneficial for CO_2 reduction? (2) If yes, does the coal-based energy consumption structure have an inhibitory effect on this reduction effect? (3) If there is such an inhibitory effect, what measures should China adopt in order to give full play to the role of *RETI* in reducing CO_2 emissions? With these questions, this paper integrates the technological innovation, energy structure and climate change into a unified framework and adopts a panel threshold model to analyze the heterogeneous role of *RETI* on CO_2 emissions under different energy structure.

In terms of indicators construction, many scholars use R&D personnel, R&D investments, R&D funding or simply patents to measure the technological innovation, ignoring the diffusion and depreciation effects during the innovation process, which will lead to certain measurement errors. Methodologically, at present, many studies adopt the traditional linear panel data model, ignoring the potential existence of non-linear relationships among economic variables, which will cause biased estimation to the empirical results. Therefore, this paper contributes to the existing literature in the following three ways: First, by using a novel approach to construct the *RETI* level, we accurately measure technological innovation level in different Chinese provinces. Second, this study additionally explores the distinct effect of *RETI* on CO_2 reduction under different energy structure by using the panel threshold model. We discover the heterogeneity effect of *RETI* in different situations, which could provide more effective evidence for policymakers. Third, this paper provides new insight into the relationship between technological innovation and climate change. Climate change is an urgent challenge facing the world. Technological innovation, especially the renewable energy technological innovation, is recognized as one of the effective ways to mitigate climate change. This paper enriches this topic and provides some valuable research idea.

The rest of this paper is organized as follows: Section 2 provides a detailed literature review about the climate changes. The model specification and data description are presented in Section 3. Section 4 is the empirical results. The last section concludes this paper with some relevant policy implications.

2. Overview

The climate change, which is mainly caused by CO_2 emissions, has become a global concern (Li and Wang, 2017; Li and Lin, 2013). Nowadays, many scholars have investigated the driving factors of CO_2 emissions, and mainly focused on the following aspects:

Previous studies about the relationship between economic growth and CO_2 emissions are mainly from the aspect of environmental EKC theory. The environmental EKC theory, which was proposed by Grossman and Krueger (1991), claimed that there is a U-shaped relationship between economic growth and environmental quality. That is, with the growth of economies, the environment will be deteriorated at the beginning, but once the economy develops to a certain stage, the environmental quality will be improved. Based on this theory, many scholars have explored whether this theory is established from different countries, different time level by using different econometrical methods (Lin and Zhu, 2017; Kaika and Zervas, 2013; Ahmad et al., 2017; Apergis, 2016).

The impact of structural changes on CO_2 emissions is another issue that has gained the attention of scholars concerned. The structural changes we mentioned here contain two aspects: changes in energy consumption structure and changes in industrial structure. Compared with renewable energy, the combustion process of traditional fossil fuel energy will emit a lot of greenhouse gases (IPCC, 2015), and the existing literature has proved that the fossil fuel-based energy consumption structure is the main reason for climate changes (Lin et al., 2010; Wang et al., 2016; Yao et al., 2018; Huang et al., 2018). Another topic focuses on changes in the industrial structure. China's industrial sectors have three classes, the secondary industrial, which is energy-intensive industry, consumes a large amount of energy and leads to serious environmental pollution (Li and Lin, 2015). Therefore, adjusting industrial structure is suggested for energy-saving and emission-reduction (Lin and Zhu, 2017; Cheng et al., 2018; Li et al., 2017; Xu and Lin, 2015; Zhou et al., 2013).

The urbanization process is a social phenomenon that people migrate from the rural area to the city (Zhang et al., 2017). The impact of urbanization process on CO_2 emissions is a hot issue, and more and more scholars have investigated this impact. Some scholars found that that the urbanization process increases CO_2 emissions (Al-mulali et al., 2012; Parikh and Shukla, 1995; Zhu and Peng, 2012). However, some scholars found that there is a nonlinear relationship between urbanization and CO_2 emissions. Based on the data of 141 countries from 1961 to 2011, Zhang et al. (2017) adopted the extended STIRPAT to investigate the effect of urbanization on CO_2 emissions, they found that there is an inverted U-shaped effect from urbanization to CO_2 emissions. This is also found in Xu and Lin (2015), Maruotti (2008). Some other scholars, such as Rafiq et al. (2016) and Sadorsky (2014) argued that the urbanization process has an insignificant effect on CO_2 emissions.

The technological innovation process, which is our concern and recognized as an efficient way for mitigating climate change, is a substantially interesting issue. For example, Li and Wang (2017) mentioned that hindering CO_2 emissions in the production process is an efficient way to alleviate climate change. Based on the data of 95 countries from 1996 to 2007, they applied a novel approach by considering the effect of technological innovation on economic growth and CO_2 emissions and revealed that that technological innovation has a significant negative effect on CO_2 emissions. Su and Moaniba (2017) indicated that in order to mitigate climate changes, society should pay attention to innovation activities.

The renewable energy technologies, which are recognized as energy conservation and low carbon technologies, have been widely researched in the existing literature (Zhang et al., 2014; Kalt and Kranzl, 2011; Patsialis et al., 2016). It is worth for us to pay attention to the role of renewable energy and *RETI* on CO_2 reduction. Kamoun et al. (2017) investigated the role of *RETI* on sustainable growth, they found the *RETI* has a significant role on a sustainable growth path and suggested that the society should stimulate *RETI*. Chen and Lei (2018) explored the effect of renewable energy and technological innovation on CO_2 emissions, they argued that the limited reduction effect of renewable energy is mainly caused by the smaller proportion of renewable energy in total energy consumption.

In summary, existing literature has explored different drivers of CO_2 emissions. And also some researchers have analyzed the effect of renewable energy, *RETI*, and CO_2 emissions, but they ignored the influence of the changes in society, especially the changes in energy structures. In addition, to the best of our knowledge, this is the first paper to explore the relationship among *RETI*, energy structure and CO_2 emissions from the Chinese perspective. Considering that China is the largest energy consumer and CO_2 emitter, it is really important to undertake this study. Therefore, based on the previous studies, we carry out this work and attempt to put forward some useful policy recommendation for China. Besides, this work also can expand existing literature to understand the relationship between technological innovation and CO_2 emissions.

3. Model specification and data descriptive

3.1. Environmental Kuznets curve (EKC) of CO_2 emissions

Most scholars have used the extended EKC model to explore the influencing factors of CO_2 emissions. The EKC model is put forward by Grossman and Krueger (Intergovernmental Panel on Climate Change, 2015), they found that there exists an inverted U-shaped relationship between income level and pollutants. The simple EKC model of CO_2 emissions reveals the relationship between income level and CO_2 emissions. We use the quadratic equation form model with the per capita income as the explanatory variable (Shafik and Bandyopadhyay, 1992; Lin and Zhu, 2018) and we extend this model by adding some driving factors. The model is expressed as follows:

$$\ln PCCO_2 = \alpha_i + \alpha_1 \ln RPCGDP + \alpha_2 (\ln RPCGDP)^2 + X'\beta + \varepsilon \tag{1}$$

where $PCCO_2$ is per capita CO_2 emissions, *RPCGDP* is per capita real GDP, X is a vector for driving factors and ε is random error term. When $\alpha_1 > 0$, $\alpha_2 < 0$ then we determine that there is a U-shaped relationship between CO_2 emissions and income level. Because we want to analyze the role of *RETI* on CO_2 emissions, so we add it in Eq. (1), and the following equation was obtained:

$$\ln PCCO_2 = \alpha_i + \alpha_1 \ln RPCGDP + \alpha_2 (\ln RPCGDP)^2 + \beta_1 \ln RETI + \sum_{j=2}^{K} X_j{}'\beta_j + \varepsilon \tag{2}$$

where *RETI* represents the renewable energy technological innovation. X are other control variables, the detailed data descriptive statistics are presented in Section 3.2.

3.2. Data

3.2.1. Dependent variable

Per capita CO_2 emissions ($PCCO_2$). Due to the reason that there is no provincial CO_2 emissions data in Chinese database, we need to calculate it by using different fossil energy consumption. The IPCC has provided the CO_2 emissions coefficients of different fossil energy, the detailed calculation formula can be found in Lin and Zhu (2017). Dividing total CO_2 emissions by population can obtain $PCCO_2$. The relevant energy data was obtained from China Energy Statistics Yearbook, and the population data come from China Statistics Yearbook.

3.2.2. Core variables

This paper takes the $PCCO_2$ as the study object. According to the above analysis on the relationship between *RETI* and CO_2 emissions, the development of *RETI* is not only conducive for the development of renewable energy, but also plays an important role in the development of low-carbon society. So based on the EKC theory, this paper attempt to analyze the effect of *RETI* and energy structure on CO_2 emissions reduction. The core variables include per capita income, *RETI*, and energy structure.

(1) Per capita income (*RPCGDP*). We use the per capita real GDP as the proxy of per capita income. We first obtain the real GDP which is normalized at 2000 constant price by using the GDP index, and then dividing the real GDP by total population can obtain *RPCGDP*. All relevant data were obtained from China Statistics Yearbook.

(2) Renewable energy technological innovation (*RETI*). Using renewable energy patents as the innovation of renewable energy are widely adopted in the existing literature. However, due to the great differences between different patents, nowadays many scholars have constructed the indicator as the technological innovation by using renewable patents (Verdolini and Galeotti, 2011; Yan et al., 2017). This paper complies with the calculation method which was proposed by Popp (2002) because his method considers the depreciation rate as well as the diffusion rate of the patents, which is as follows:

$$RETI_{it} = \sum_{j=0}^{t} RPAT_{ij}\ \exp[-\beta_1(t-j)] \cdot \{1 - \exp[-\beta_2(t-j)]\} \tag{3}$$

where, *RPAT* is the authorized renewable energy patents, β_1 and β_2 are the depreciation rate (0.36) and diffusion rate (0.3) respectively (Popp, 2002). The data on renewable energy patents authorized was obtained from the Patent Search and Analysis (PSA) system of the China's National Intellectual Property Administration (CNIPA).[2] The PSA system is the official patent search system in China. It contains patent data of 103 countries, regions or organizations. Therefore, the data are comprehensive and authoritative in this system. The renewable energy we analyzed in this paper includes wind power, solar energy, marine (ocean) energy, hydropower, biomass energy, and storage. We search for this by using the latest International Patent Classification (IPC) code (See Appendix A). Fig. 2 shows the *RETI* of Chinese provinces in 2005 and 2015, the figure reveals that the *RETI* level has increased significantly. We also observe that there exists a huge difference in *RETI* across Chinese provinces.

(3) Energy structure. Energy structure includes energy consumption structure (*ENS*) and the proportion of renewable energy generation (*NEW*). China's coal-dominated energy structure is the main source of pollutants and greenhouse gas, which also gives rise to a serious threat to energy security and energy dependency (Hao et al., 2015). The development of renewable energy is an efficient way to relieve environmental pressures and build a safe, independent and sustainable energy system (Wang et al., 2018). So we choose the *ENS* and *NEW* as the core variables and explore their impact on CO_2 emissions. The *ENS* is calculated by dividing coal consumption to the total energy consumption, and the *NEW* is the ratio of the renewable energy generation to total electricity generation. The renewable energy generation was provided by Xu and Lin (2018) and other relevant data was obtained from the China Energy Statistics Yearbook.

[2] http://www.pss-system.gov.cn/.

3.2.3. Control variables

(1) Urbanization rate (*Urb*). One of the significant features of Chinese economics and society is the rapid urbanization process. Chinese urbanization rate was 19.92% in 1978 but increased to 57.35% in 2016. China's rapid urbanization process has made China face severe energy and environmental pressures (Zhang et al., 2017). As the concentration of population, construction, transportation and industry, the normal operation of the city requires a lot of energy as the support, so it also emits a large number of greenhouse gases. Following the existing literature, we select the urbanization rate as one control variable, and we measure it by using the proportion of urban population in the total population. The relevant data come from China Provincial Statistics Yearbook.

(2) Industrial structure (*SI*). We use the proportion of the output added value of the secondary industry as the proxy of industrial structure. Another significant feature of the Chinese economy is its deep industrialization. The Chinese statistics reveal that the proportion of the secondary industry was 47.7% in 1978 but still remained at 39.8% in 2016. The secondary industry consumed almost 70% (69.77%) of China's total energy consumption in 2016. So the change of the secondary industry will have a significant impact on energy consumption as well as CO_2 emissions (Lin and Zhu, 2017; Zhang and Lin, 2012). We collect the relevant data from China Statistics Yearbook.

Due to the data limitation, this paper uses China's 30 provincial balanced panel data from 2000 to 2015, Tibet, Hong Kong, Macao, and Taiwan are not included in our analysis. The statistical descriptions of all variables are presented in Table 1.

Because technological innovation has the characteristic of hysteresis, which means that there is a lag time for technological innovation to work inevitably. Therefore, the effect of *RETI* on CO_2 emissions has a certain time lag. This paper selects the first-order lagged terms of *RETI* as an explanatory variable and based on Eq. (2), we build the following static panel data model:

$$\begin{aligned} \ln PCCO_{2,it} = {} & \alpha_i + \alpha_1\ \ln RPCGDP_{it} + \alpha_2(\ \ln RPCGDP_{it})^2 + \beta_1\ \ln RETI_{i,t-1} \\ & + \beta_2\ \ln ENS_{it} + \beta_3\ \ln NEW_{it} + \beta_4\ \ln URB_{it} + \beta_5\ \ln SI_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

4. Empirical analysis

4.1. Panel data tests

Before constructing the panel regression models, we need to test the stability of all variables. Considering the limited time span of all variables, this paper adopts the IPS test and LLC test, which both assume that there is unit root in their null hypothesis. We also adopt CIPS test, which allows for cross-sectional dependence (Pesaran, 2007).[3] The results of the panel unit root test (See Table 2) reveal that the first difference of all variables is stationary.

In addition, we apply a co-integration test for CO_2 emissions and its drivers. We adopt the Kao residual co-integration test, which is proposed by Kao (1999). The null hypothesis of the Kao test assumes that there is no co-integration among these variables. The results of Kao test (the t-Statistic is −5.719 and p-Value is 0.000) reveal the existence of co-integration relationship among these variables, hence a further econometrical analysis is carried out.

4.2. Linear regression analysis

Based on Eq. (4), we used the static panel analysis to run the regression, which includes fixed effects (FE) model and random effects (RE) model, and the results are showed in Table 3. In order to determine which model should be selected, we also reported the result of the

[3] We thank the anonymous reviewer for this important suggestion.

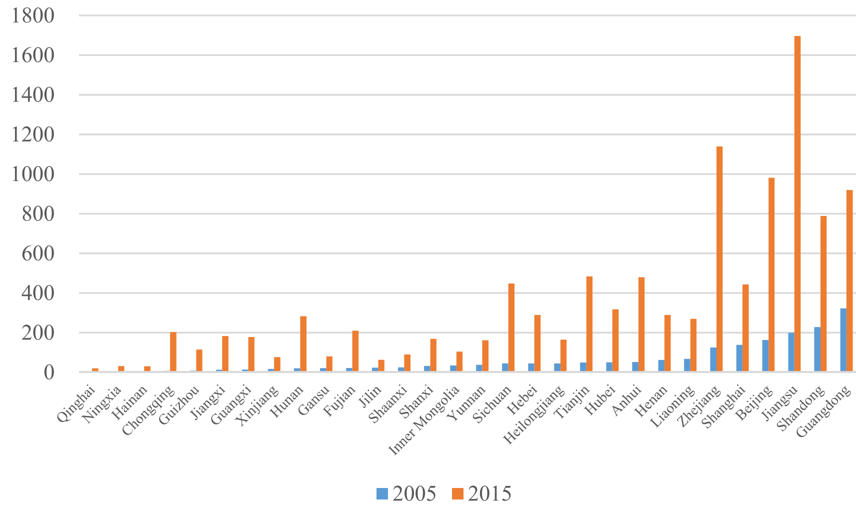

Fig. 2. *RETI* of Chinese provinces in 2005 and 2015.

Hausman test. The *p*-value of the *Hausman test* is 0.077, so we cannot reject the RE model at 5% significant level, indicating that there is no obvious difference between these two models. Actually, the coefficients of these models are really quite similar. In addition, we also report the result of Fully-Modified OLS (FMOLS) model, which is reported in the third column of Table 3.

From the results in Table 3. We observe that there is a significant negative effect from *RETI* to CO_2 emissions, which indicates that the increase of *RETI* is beneficial for CO_2 reduction. The coefficient of *RETI* is around −0.045, meaning that every 1% increase of last period *RETI*, the current $PCCO_2$ will decrease by 0.045%. The coefficient of *lnRPCGDP* is significantly positive and the coefficient of $(lnRPCGDP)^2$ is significantly negative, confirming that the existing of EKC curves for CO_2 emission.

Even though the renewable energy generation (*lnNEW*) is negatively correlated with CO_2 emissions, but the coefficient is small and nonsignificant in all cases. This proves that the development of renewable energy is beneficial for China to a low-carbon economy, but the small effect may be due to the limited proportion of renewable energy in the total energy (Chen and Lei, 2018). Energy consumption structure (*lnENS*) has a significant and positive effect on CO_2 emissions, which confirms that the cause of the relatively high CO_2 emissions is the coal-dominated energy structure and this is consistent with the existing literature. Besides, the industrial structure variable (*lnSI*) is significant and positive, which is in line with reality. It is noteworthy that, the coefficient of urbanization rate (*lnUrb*) is not significant, meaning that the impact of urbanization on CO_2 emissions is negligible. Even though the result is the opposite of some literature, but a similar result can be found in Rafiq et al. (2016) and Sadorsky (2014).

4.3. Threshold effect

Existing literature has proved that the energy structure has a nonlinear effect on renewable energy development (Xu and Lin, 2018), and the coal-dominated energy structure will hinder the development of renewable energy. However, the renewable energy is conducive to reducing CO_2 emissions and mitigating climate change (Lin et al., 2010; Wang et al., 2018), so it is really important to determine whether there is a non-linear relationship between *RETI* and CO_2 emissions under different energy structures. In order to explore this impact, we adopt the panel threshold model for further analysis.

Hansen (1999) first put forward the static panel threshold model and adopted strict statistical inference methods for parameter estimation and statistical inference of threshold values. For panel data $\{Y_{it}, X_{it}, q_{it}: 1 \le i \le n, 1 \le t \le T\}$, considering the following fixed effect single threshold model:

$$\begin{cases} Y_{it} = \alpha_i + \beta_1{}' X_{it} + \varepsilon_{it}, & if \ \ q_{it} \le \gamma \\ Y_{it} = \alpha_i + \beta_1{}' X_{it} + \varepsilon_{it}, & if \ \ q_{it} > \gamma \end{cases} \tag{5}$$

where, q_{it} is the threshold variable. γ is the threshold. ε_{it} is a residual term and assumed to be independent and identically distributed. u_i is the individual effect. The existing of u_i means that this is a fixed effects model. If we use the indicator function $I(\cdot)$, then Eq. (5) can be simplified as follows:

$$Y_{it} = \alpha_i + \beta_1{}' X_{it} \cdot I(q_{it} \le \gamma) + \beta_2{}' X_{it} \cdot I(q_{it} > \gamma) + \varepsilon_{it} \tag{6}$$

When the condition in brackets is satisfied, then $I(\cdot) = 1$, otherwise $I(\cdot) = 0$. We can test the following null hypothesis to verify whether there exists threshold effect:

$$H_0 : \beta_1 = \beta_2 \tag{7}$$

If we cannot reject the null hypothesis, then the threshold model can be simplified to the following linear model:

$$Y_{it} = \alpha_i + \beta_1{}' X_{it} + \varepsilon_{it} \tag{8}$$

For this standard fixed effect model, it can be transformed into a deviation form and then estimated by OLS. We can use the LR test, which was provided by Hansen (1999), to judge whether the threshold effect really exists. The LR statistics are as follows:

$$LR = [SSR^* - SSR(\hat{\gamma})]/\hat{\sigma}^2 \tag{9}$$

where SSR^* is residual sum of squares under the null hypothesis H_0: $\beta_1 = \beta_2$. $SSR(\hat{\gamma})$ is residual sum of squares with no constraint. $\hat{\sigma}^2 = \frac{SSR(\hat{\gamma})}{n(T-1)}$ is an unbiased estimator of ε_{it}.

Table 1
Statistical description of variables.

Variable	Unit	Obs	Mean	Std. dev.	Min	Max
$PCCO_2$	Tonnes/person	480	6.944	5.402	0.943	32.788
RPCGDP	Yuan/person	480	20,478.710	14,933.520	2742.010	84,533.300
RETI	–	480	187.832	321.836	0.267	2457.870
ENS	%	480	64.949	17.924	12.145	99.300
NEW	%	480	20.489	22.800	0.001	89.132
URB	%	480	48.878	15.235	23.200	89.610
SI	%	480	46.942	7.662	19.740	61.500

Table 2
Panel unit root test.

	Series	IPS test (Wt-bar)		LLC test (Adjusted t*)		CIPS test (Zt-bar)	
		Constant	Trend and constant	Constant	Trend and constant	Constant	Trend and constant
Levels	*lnPCCO$_2$*	−1.848**	−1.352*	−3.835***	5.9978***	−2.367***	−2.730**
	lnRPCGDP	1.246	0.099	−4.882***	−7.262***	−1.059	−2.032
	lnRPCGDP^2	−0.036	−0.382	−6.397***	−7.299***	−1.552	−2.065
	lnRETI	−8.059***	−7.598***	−10.354***	−10.590***	−3.355***	−3.710***
	lnNEW	0.442	−0.778	−2.2856**	−6.312***	−2.370***	−2.726**
	lnENS	1.190	−2.620***	−0.0560	−7.598***	−2.056	−2.062
	lnUrb	−2.047*	−1.618*	−6.100***	−6.701***	−1.972	−2.379
	lnSI	2.712	3.518	−1.149	−2.378***	−1.803	−2.051
First difference	*D.lnPCCO$_2$*	−13.041***	−11.126***	−16.106***	−16.152***	−3.694***	−3.753***
	D.lnRPCGDP	−2.617***	−0.190	−4.792***	−4.941***	−2.177**	−2.485
	D.lnRPCGDP^2	−1.819**	−0.363	−4.170***	−4.987***	−2.207**	−2.485
	D.lnRETI	−19.232***	−16.852***	−21.106***	−19.742***	−4.823***	−5.059***
	D.lnNEW	−16.895***	−13.700***	−22.132***	−19.453***	−4.183***	−4.504***
	D.lnENS	−14.821***	−12.894***	−19.773***	−19.045***	−3.273***	−3.359***
	D.lnUrb	−10.474***	−7.936***	−12.144***	−11.961***	−3.204***	−3.211***
	D.lnSI	−8.572***	−6.674***	−11.932***	−11.873***	−2.973***	−2.679*

Note: (1) For IPS and LLC tests, lag length selection based on AIC criterion; (2) For CIPS test, the maximum is set to 3 and BG lag is set to 9.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Similarly, we consider the multi-threshold panel regression model and take the double threshold values model as an example:

$$Y_{it} = \alpha_i + \beta_1{}'X_{it} \cdot I(q_{it} \le \gamma_1) + \beta_2{}'X_{it} \cdot I(\gamma_1 < q_{it} \le \gamma_2) + \beta_3{}'X_{it} \cdot I(q_{it} > \gamma_2) + \varepsilon_{it} \tag{10}$$

where, γ_1 and γ_2 are threshold values and $\gamma_1 < \gamma_2$.

Following the static panel threshold model proposed by Hansen (1999), this paper chooses the energy structure variables (*lnENS* and *lnNEW*) as the threshold variables and regards the $lnRETI_{t-1}$ as the explanatory variable. We first need to specify the threshold number and threshold value when using different threshold variables. The results are shown in Tables 4 and 5 respectively. The results confirm that there are double threshold effects when choosing the *lnENS* as the threshold variable, but there is only one threshold effect when regarding the *lnNEW* as the threshold variable. We hence construct the threshold modes as follows:

$$\begin{aligned} \ln PCCO_{2,it} = {} & \alpha_i + \beta_1 \ \ln RETI_{i,t-1}(\ \ln ENS_{it} \le \gamma_1) + \beta_2 \ \ln RETI_{i,t-1}(\gamma_1 < \ln ENS_{it} \le \gamma_2) \\ & + \beta_3 \ \ln RETI_{i,t-1}(\gamma_2 < \ \ln ENS_{it}) + \beta_4 \ \ln NEW_{it} + X_{it}{}'\varphi + \varepsilon_{it} \end{aligned} \tag{11}$$

$$\begin{aligned} \ln PCCO_{2,it} = {} & \alpha_i + \beta_1 \ \ln RETI_{i,t-1}(\ \ln NEW \le \tau_1) + \beta_2 \ \ln RETI_{i,t-1}(\tau_1 < \ \ln NEW) \\ & + \beta_3 \ \ln ENS + X'\varphi + \varepsilon_{it} \end{aligned} \tag{12}$$

We adopt the bootstrap method to test the threshold effect with 1000 repeated simulations. The results are presented in Tables 4 and 5. When regarding *lnENS* as the threshold variable, the first and second threshold value are 3.9917 and 4.2717 respectively, and significant at 1% level. When considering the *lnNEW* as the threshold variable, the only one threshold value is 2.6537 and significant at 10% level.

The threshold estimation results are presented in Table 6. Model (4) is the estimation result with the *lnENS* as the threshold variable. 3.9917 and 4.2794 are two threshold values and correspond to 54.15 and 72.20 when converted to normal values. The results show that under different energy consumption structures, the effects of renewable energy technological innovation on CO_2 reduction are different at different threshold interval. When the *ENS* is <54.15%, a 1% rise in last period *RETI* will reduce the current CO_2 emissions by 0.085%. But this effect decreases with the increase of *ENS*. When the *ENS* is between 54.12% and 72.20%, the coefficient of last period *RETI* becomes to −0.044. What's more, when the *ENS* is >72.20%, the effect of last period *RETI* on current CO_2 emissions is even insignificant. One reasonable explanation may be, the coal-dominated energy consumption structure is harmful to the CO_2 reduction effect of Chinese renewable energy technological innovation. These provinces, which are heavily dependent on fossil energy, may not pay enough attention to the role of *RETI*. This will hinder the transformation of the *RETI* achievements, and ultimately affect the reduction effect of *RETI*.

Table 3
Static panel regression results.

	Model (1)	Model (2)	Model (3)
	FE	RE	FMOLS
lnRPCGDP	2.026***	2.097***	1.956***
	(0.000)	(0.000)	(0.001)
lnRPCGDP^2	−0.065***	−0.068***	−0.061**
	(0.001)	(0.000)	(0.035)
lnRETI$_{t-1}$	−0.045***	−0.048***	−0.040**
	(0.001)	(0.000)	(0.049)
lnNEW	−0.003	−0.003	−0.001
	(0.720)	(0.773)	(0.9899)
lnENS	0.767***	0.782***	0.783***
	(0.000)	(0.000)	(0.000)
lnUrb	0.223	0.173	0.083
	(0.134)	(0.214)	(0.714)
lnSI	0.492***	0.490***	0.417***
	(0.000)	(0.000)	(0.000)
Constant	−17.447***	−17.725***	
	(0.000)	(0.000)	
N	450	450	420
Within R^2	0.896	0.896	0.967
Hausman test	12.79 (0.077)		

Note: *p*-values in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Threshold effect test based on Eq. (11).

Threshold variable	Threshold number	F-statistics	*p*-Value	Threshold value	Confidence intervals (95%)
lnENS	Single	75.60	0.001	3.9917	[3.9782, 3.9924]
	Double	51.42	0.006	4.2794	[4.2774, 4.2816]

Table 5
Threshold effect test based on Eq. (12).

Threshold variable	Threshold number	F-statistics	p-Value	Threshold value	Confidence intervals (95%)
lnNEW	Single	27.92	0.063	2.6537	[2.6169, 2.6542]

Model (5) is the estimation result with the *lnNEW* as the threshold variable. There are two intervals which are $lnNEW \le 2.6537$ and $2.6537 < lnNEW$. The *RETI* is significantly and negatively correlated with CO_2 emissions both in these two intervals with a gradually increasing effect. The coefficient of last period *RETI* is −0.033 when the $lnNEW \le 2.6537$, but this negative effect increases to −0.061 when $2.6537 < lnNEW$. By calculation, 2.6537 corresponds to a threshold value of *NEW* equal to 14.21. The increasing negative effect of *RETI* on CO_2 emissions indicates that with the increase in renewable energy generation, the *RETI* will play a more and more important role in CO_2 reduction. On the one hand, the role of renewable energy technology innovation will be emphasized in these provinces with high renewable energy utilization. Then, the development of renewable energy will make the society focus more on the role of *RETI*, which eventually encourage government and enterprises to invest more in the transformation of *RETI*. On the other hand, *RETI* will contribute to the improvement of renewable energy technologies and then further promote the development of renewable energy. Considering the important role of renewable energy in low-carbon society, the development of renewable energy is conducive for making full use of the role of *RETI* in CO_2 reduction.

5. Conclusions and policy recommendations

Using China's provincial panel data from 2000 to 2015, and regarding the CO_2 emissions as the proxy of climate change, this paper identifies the relationship between *RETI* and CO_2 emissions as well as seeks to confirm the role of *RETI* on climate change. We obtain the following main conclusion:

Table 6
Estimation results of threshold models.

	Model (4)	Model (5)
	Threshold variable: lnENS	Threshold variable: lnNEW
lnRPCGDP	1.450*** (0.001)	2.022*** (0.000)
$lnRPCGDP^2$	−0.0411* (0.057)	−0.065*** (0.000)
lnUrb	0.392** (0.016)	0.240* (0.093)
lnSI	0.779*** (0.000)	0.504*** (0.000)
lnNEW	−0.008 (0.438)	
$lnRETI_{t-1}$ ($lnENS \le 3.9917$)	−0.085*** (0.000)	
$lnRETI_{t-1}$ ($3.9917 < lnENS \le 4.2794$)	−0.044*** (0.002)	
$lnRETI_{-1}$ ($4.2794 < lnENS$)	0.0008 (0.957)	
lnENS		0.758*** (0.000)
$lnRETI_{t-1}$ ($lnNEW \le 2.6537$)		−0.033** (0.01)
$lnRETI_{t-1}$ ($2.6537 < lnNEW$)		−0.061*** (0.000)

Note: p-values in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

(1) The results of linear regression show that there is a significant and negative effect from *RETI* to CO_2 emissions, which means that the *RETI* is beneficial for a low-carbon society. Meanwhile, Considering the role of energy structure, the coal-dominated energy structure is a major factor in increasing the CO_2 emissions. In contrast, the proportion of renewable energy generation is helpful to CO_2 reduction, but the impact is insignificant and even negligible in the linear regression model, we attribute this to the small proportion of renewable energy in total energy consumption.
(2) The threshold tests confirm that there are double threshold effects when taking the *ENS* as the threshold variable, but only one threshold effect when regarding the *NEW* as the threshold variable. This means that the *RETI* has threshold effect under different energy structure. Specifically, we observe that the CO_2 reduction effect of *RETI* decreases with the rising of *ENS*. In contrast, this effect increases with the growing of *NEW*. These findings confirm that the coal-dominated energy consumption structure will hinder the CO_2 reduction effect of *RETI*.

It is self-evident that renewable energy is irreplaceable in China's low-carbon society. This paper discusses the relationship between *RETI* and CO_2 emissions in the transition period of China towards clean and low carbon energy society, which has some significant policy implications to make full use of the *RETI* on CO_2 reduction.

On the one hand, each province should pay enough attention to the role of *RETI*, especially for those with a higher proportion of fossil energy consumption and a lower proportion of renewable energy generation. The results of our paper have confirmed the important role of *RETI* on CO_2 reduction, however, this effect is really different in provinces with different energy structures. These provinces with higher fossil energy consumption should do their best to promote the transformation of the *RETI* achievements, create favorable environments and conditions to bring the role of *RETI* into full play, and eventually accelerate the industrialization of renewable energy technology and its application.

On the other hand, promoting the use of renewable energy. Under the current technical level and the price system, the different competitiveness between the large-scale use of renewable energy and conventional fossil energy is mainly due to the different costs. Our empirical results reveal that the use of renewable energy is beneficial for climate change, but this effect is small and even insignificant in some models. Therefore, it is an efficient way for China to promote the use of renewable energy. Considering China's energy consumption structure, it will take some time for large-scale use of renewable energy in electricity generation to be realized. However, the government can encourage the use of renewable energy in residential life and production process. For example, popularizing the use of solar water heater, further expanding the use of biomass energy in rural areas and promoting the use of renewable energy such as solar energy and geothermal energy in green buildings.

Our findings could be a useful step better understand the role of technological innovation on climate change, but much remains to be done. First, more indicators on measuring the *RETI* is needed in the future study. Even though we measure the *RETI* in a novel approach, but technological innovation contains many aspects, such as R&D personnel and R&D investments. Second, the model approach can be further optimized. This paper only considers the linear and threshold effect of the *RETI* on CO_2 emissions. However, the impact of *RETI* on CO_2 emissions is really complicated. Therefore, a comprehensive model is needed in future research.

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Appendix A

Technology	IPC classes
Wind power	F03D
Solar energy	F03G6; F24J2; F26B3/28; H01L27/142; H01L31/042-058
Marine (ocean) energy	E02B9/08; F03B13/10–26; F03G7/05
Hydro power	E02B9 and not E02B9/08; [F03B3 or F03B7 or F03B13/06-08 or F03B15] and not F03B13/10-26
Biomass energy	C10L5/42–44; F02B43/08
Storage	H01M10/06-18; H01M10/24–32; H01M10/34; H01M10/36–40

Sources: Noailly and Shestalova (2017), Johnstone and Haščič (2010), Johnstone et al. (2010).

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