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Research article

Determinants of renewable energy technological innovation in China under CO_2 emissions constraint

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ABSTRACT

Renewable energy is not only an efficient way to ensure energy independence and security but also supports the transition to a low carbon economy and society. The progress of renewable energy technological innovation is an important factor that influences the development of renewable energy. An in-depth analysis of the driving factors that influence this progress is crucial to China's energy transition. Based on Chinese provincial data over 2000–2015 and panel data models, this paper regards the CO_2 emissions as climate change and explores the response of renewable energy technological innovation to intensive CO_2 emissions. We also analyze the effect of the driving factors such as energy price and R&D investment on this innovation process. The main conclusions drawn are: (1) There are significant differences in technological innovation levels across China's provinces. (2) We observe that the intensive CO_2 emissions have promoted renewable energy technological innovation level, meaning that innovation process responds actively to climate changes. (3) R&D investment from government and enterprise both are conducive for promoting the innovation level. (4) Energy price has an insignificant effect on innovation in renewable energy technologies and we attribute this to the unreasonable energy price mechanism. This paper provides clear evidence for understanding the role of innovation on climate change.

1. Introduction

China's coal-dominated energy consumption structure has a huge impact on energy security, energy independence and environmental pollution (Ren and Sovacool, 2014; Hao et al., 2015; Yang et al., 2018). According to BP statistics, China's total energy consumption was 3053 million tonnes oil equivalent (Mtoe) in 2016. Where, total coal consumption was 1887.6 Mtoe, accounting for 61.8% of total energy consumption. The long-term coal-dominated energy consumption structure emits large amounts of CO_2 (Lin and Zhu, 2017; Shao et al., 2014). BP statistics also show that China's total CO_2 emissions were 9123 million tonnes in 2016, accounting for 27.3% of the total world. Considering energy independence and security, China's fossil energy consumption is currently growing rapidly. According to IEA data, China's coal, oil, and natural gas reserve-production ratio were only 72, 17.5, and 38.8 in 2016, which means that under the general production condition, the three fossil energy sources are only available for 72, 17.5 and 38.8 years respectively and far below the world average.

Renewable energy is of great significance for China to build a safe, independent and low-carbon energy system (Yao and Chang, 2014; Ren and Sovacool, 2014; Wang et al., 2018). The increasing depletion of traditional fossil energy and the pressure for energy saving and emission reduction have forced China to develop renewable energy (Li and Lin, 2017). According to data from the Chinese government, the installed capacity of hydropower, wind power, photovoltaic power generation, and biomass power generation reached 338 million kW, 154 million kW, 102 million kW and 13.3 million kW respectively, and ranked first in the world.[1] However, even though China is currently experiencing rapid renewable energy development. Due to market failures and some other reasons, the development of renewable energy is facing some problems. First, due to the high upfront cost, the development of renewable energy requires a high initial investment (Kim and Park, 2016) and large amounts of government subsidies (Zhang et al., 2017a). To achieve sufficient market competitiveness for renewable energy, it is necessary to further promote renewable energy technological innovation (*RETI*) level. Second, although China currently has relatively higher technological R&D ability in hydropower, nuclear power, and thermal power, it has weaker innovation

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[1] http://www.gov.cn/xinwen/2017-09/23/content_5227157.htm#1.

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capabilities in wind power, biomass, etc. Third, even though the *RETI* develops fast, there are still great differences among China's provinces. Understanding the reasons for such regional differences are beneficial to China in developing renewable energy and building a low carbon and safe modern economic system.

The existing studies mainly focus on the effect of technological innovation on CO_2 reduction (Jia et al., 2018; Liu and Liang, 2017). Few studies consider it from the opposite direction, in other words, whether intensive CO_2 emissions promote *RETI* level. In order to validate this idea, this paper adopts various econometric methods to assess the response of *RETI* to CO_2 emissions. Based on Chinese provincial panel data from 2000 to 2015, this paper commences with constructing the *RETI* level of Chinese provinces. Then using panel data analysis, this paper explores the effect of the driving factors on China's *RETI* by taking the CO_2 emissions constraint into account. We obtain a reliable conclusion after conducting the robustness test. Finally, the paper proposes several relevant policy recommendations.

We make the following contributions. First, even though some prior studies have researched the relationship between technological innovation and climate change, they focused on the country level (Su and Moaniba, 2017). Conducting the research from China's perspective is more targeted and representative due to the fact that China is the largest carbon emitter and energy consumer (Yao et al., 2018; Tian et al., 2019). By using various econometrics models and considering the role of CO_2 emissions, we explore the driving factors that cause differences in *RETI* among China's provinces. This will support the provinces in proposing the development strategy according to local conditions and ensure the *stable* development of China's renewable energy. Second, this paper adopts a novel way to explore the relationship between low-carbon technological innovation and climate changes by examining how Chinese *RETI* responses to intensive CO_2 emissions, which contributes to the existing literature on further understanding the role of innovation on climate change. Third, even though this paper is conducted from the perspective of China, we provide some useful information for global environmental governance since the climate change is a global concern. To learn from China's case, it is possible to formulate some targeted strategy to promote the progress of *RETI* for countries facing serious pressure on emission reduction.

The rest of this paper is proceeded as follows (see Fig. 1). Section 2 summarizes the existing literature about renewable energy and technological innovation. Section 3 is model specification and data description. Section 4 presents empirical analysis. Section 5 concludes this paper with some relevant policy implications.

2. Literature reviews

2.1. The role of renewable energy

Global climate change and the depletion of traditional fossil energy have reinforced the importance of renewable energy. With the promotion of energy technological innovation and economic development, the global energy transition is accelerating (Solomon and Krishna, 2011). BP statistics show that renewable energy consumption accounted for 14.48% of the total energy in 2016. The rapid development of renewable energy has made a profound impact on the economy and society. Xu and Lin (2018a) found that economic growth has a positive "U" shape relationship with new energy sources. Narayan and Doytch (2017) used panel data of 89 countries and explored the relationship between energy and economic growth. The results showed that renewable energy promotes economic growth in low and lower middle income countries. Pao et al., (2014) found a long run causality from renewable energy to economic growth. Other similar findings can be found in Kahia et al. (2016); Omri et al. (2015), and Chang et al. (2015). These studies indicate that renewable energy plays an important role in promoting economic development.

Renewable energy also plays an important role in energy security and energy independence (Proskuryakova, 2018). Energy security means that the country has a stable energy supply capacity with a reasonable energy price (Wang and Zhou, 2017) and energy independence refers to a self-sufficient energy supply capacity. Energy security and energy independence are not only related to the stable development of the economy and society but also an important factor affecting the stability of a country (Ang et al., 2015). Energy reserves and foreign energy dependence are important indicators of energy security and energy independence.

With a gradual reduction of fossil energy reserves and increasing dependence on foreign energy sources, China's energy security issues have gradually emerged. China has been the world's largest oil importer since 2015 (Geng et al., 2017). This growing dependence on foreign energy resources has seriously affected China's energy security and energy independence (Radovanović et al., 2016; Zeng et al., 2017). Renewable energy can alleviate these problems to some extent. Wang

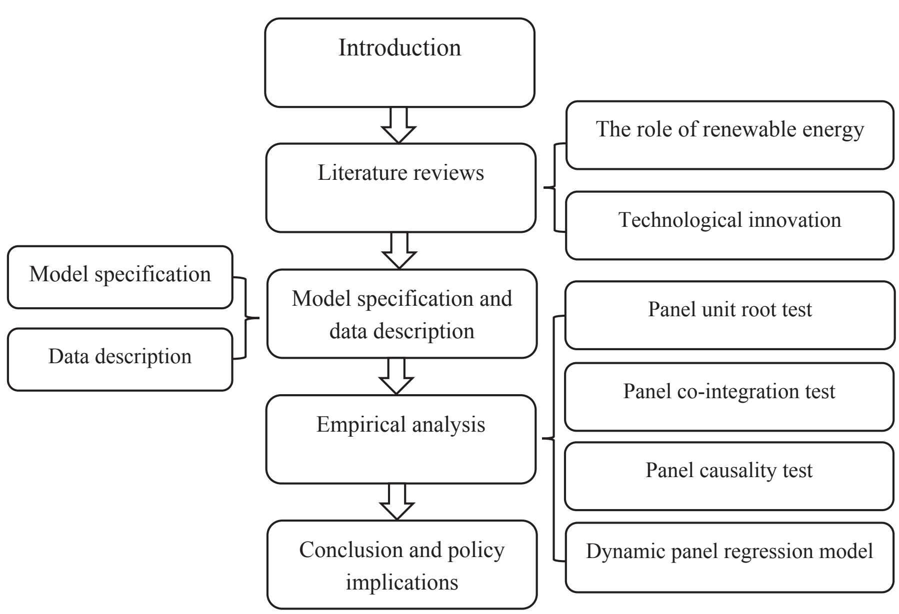

Fig. 1. Research framework.

et al. (2018) pointed out that renewable energy is an efficient way to address China's energy security. Lin and Zhu (2019) suggested that the development of renewable energy is helpful for the sustainable development of China and can also improve energy security.

Meanwhile, renewable energy can also mitigate climate change and reduce pollutant emissions. Compared with traditional fossil energy, renewable energy emits almost no pollutants. Therefore, the use of renewable energy helps to reduce greenhouse gas emissions and mitigates climate changes (Wang et al., 2018; Lin et al., 2016; Jaforullah and King, 2015; López-Menéndez et al., 2014).

2.2. Determinants of technological innovation

Prior studies on technological innovation are mainly from the aspects of innovation investment, environmental pollution, and energy consumption. Considering the role of innovation investment, it is the main innovation funding source for the whole society and plays a key role in technological innovation (Perl-Vorbach et al., 2018). Innovation investment mainly includes innovation funds and R&D personnel. Existing studies have shown that the increase in innovation input will promote technological innovation and increase the innovation output of renewable energy (Kim and Kim, 2015).

Considering environmental pollution, at present, the most serious environmental problem facing the world today is climate change, the excessive consumption of traditional fossil fuels is considered to be the source of this problem (Wu and Chen, 2018). Some studies revealed that environmental pollution can promote technological innovation. Based on the data of 70 countries, Su and Moaniba (2017) adopted several econometrical models to explore whether technological innovation responds to environmental changes. They found that CO_2 emissions from gas and liquid fuel have a positive effect on technological innovation. This point is also recognized by other scholars, Costantini and Crespi (2008) suggested that, given the active role of renewable energy in mitigating climate change, the large-scale of CO_2 emissions and other pollutants have contributed to technological progress in renewable energy. From the perspective of energy consumption and energy structure. Energy is the driving force of stable economic growth. At present, coal and oil still dominate world energy consumption structure (Key World Energy Statistics, 2016). The depletion of traditional fossil energy and the huge energy consumption have promoted the demand for new energy sources to replace fossil energy. The renewable energy industry is equivalent to a capital-intensive industry and needs lots of upfront funds for technological innovation (Xu and Lin, 2018b). Thus, the cost of renewable energy is higher than that of fossil energy (Lin and Li, 2015). We deem that the energy structure may have two effects on the development of renewable energy. In the short term, the energy consumption structure dominated by low-cost fossil energy may inhibit the technological progress of relatively expensive renewable energy. In the long run, the increasingly serious environmental problems caused by traditional fossil fuels will conversely promote the technological progress of renewable energy.

In summary, although several studies have explored the development of renewable energy, they are mainly focused on the interaction among renewable energy and economy, society, and the environment (Lin and Moubarak, 2014; Kahia et al., 2016). Furthermore, for these studies on *RETI*, many studies focus on the country level analysis and measure the innovation level by the number of renewable energy patents (Su and Moaniba, 2017), but these indicators cannot truly reflect the innovation level. Based on the data of the number of renewable energy patents, this paper accurately calculates the innovation level. Then we explore the responses of technological innovation to climate change and deeply analyze the driving factors of technological innovation, which contains targeted policy implications to improve technological innovation.

3. Model specification and data description

3.1. Model specification

In order to explore the driving factors of *RETI* in China under the CO_2 emissions constraint, we construct the following econometric model:

$$\ln RETI_{it} = \beta_o + \beta_1 \ln CO_{2,it} + \sum_{k=2}^{K} \beta_k X_{k,it} + v_i + u_t + \varepsilon_{it} \tag{1}$$

where, β_0 represents the constant, β_1, β_2, ...,β_k represent the parameters to be estimated. i represents regions, t represents year. *RETI* is renewable energy technological innovation, CO_2 is the carbon dioxide emissions and X represents the control variables. v_i is the individual effect which reflects regional differences, u_t represents the time effect, and ε_{it} is the random error term. Traditional static panel models, such as fixed-effect and random-effect models, do not consider the impact of some unobservable factors on the explanatory variables. For example, considering that technological progress is a continuous process, current technological progress is not only related to the current influencing factors, but also affected by the previous technology. As a result, using static panel model will lead to model estimation errors. We hence introduce the first-order lag items of renewable energy technology into the model and construct the dynamic panel linear regression model as follows:

$$\ln RETI_{it} = \beta_o + \alpha \ln RETI_{i,t-1} + \beta_1 \ln CO_{2,it} + \sum_{k=2}^{K} \beta_k X_{k,it} + v_i + u_t + \varepsilon_{it} \tag{2}$$

where, α represents the coefficient of ***lnRETI***, and other variables are defined identically to those in Eq. (2). The endogenous problems in the dynamic panel model make the static panel model estimation method inapplicable. We adopt the Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) generalized method of moments (GMM) estimators to estimate the dynamic panel regression model. These estimators are designed for "small T, larger N″ panels and require the dependent variable to correlate with its past values. The Arellano-Bond estimator (difference GMM) differences the estimation equation and uses the lag terms as the instrumental variables. The Arellano-Bover/Blundell-Bond estimator further assume that the first differences of the instrumental variables are uncorrelated with the fixed effect, and this is called as the system GMM estimator. The system GMM method can improve efficiency by adopting more instrumental variables (Arellano and Bover, 1995; Blundell and Bond, 1998). We adopt the system GMM estimator in the main analysis and use the code "xtabond2" which is provided by Roodman (2009).

The validity of dynamic panel GMM estimation depends on whether the selected instrumental variable is valid. There are two methods to identify the validity of the model. The first method is to use the *Sargan* (*Hansen*) test to identify the effectiveness of the instruments. The null hypothesis of these tests is that the instruments are valid. The second is to determine whether there is a second-order autocorrelation of the residual ε_{it} by using the *AR(2) test*. The hull assumption of the *AR(2)* test is that there is no second-order autocorrelation of ε_{it}.

3.2. Data description

3.2.1. Renewable energy technological innovation (RETI)

Technological innovation is an important factor for promoting the development of renewable energy (San Cristóbal, 2011), and the innovation level mainly depends on R&D investment and knowledge accumulation of renewable energy in the entire society. At present, there are two ways to measure the technological level: the first uses the R&D input or the R&D personnel to measure the technological level (Xu and Lin, 2018a). We avoid the above ways for two reasons. Firstly, R&D

input or R&D personnel cannot properly reflect the current technological level, because enterprises still have informal R&D activities, and there is no complete linear relationship between R&D investment and output. Secondly, the R&D inputs or R&D personnel data for renewable energy are not available at the provincial level.

The R&D output, measured by the number of patents, is a good measure of the technological level and is being adopted by an increasing number of scholars. However, there are some shortcomings in directly measuring the technological level based on the number of patents because patent quality may be different. Moreover, scholars currently constructed a knowledge stock and only considered the depreciation rate, but ignored the diffusion rate (Bottazzi and Peri, 2007; Yan et al., 2017; Verdolini and Galeotti, 2011). The patents which are open across on the Internet require some time to complete the transition from patent to technology. Thus, it is necessary to consider the diffusion rate of knowledge because it measures the time of large-scale application of new technologies. Popp (2002) calculated the knowledge stock by considering the diffusion and depreciation rate. The formula 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, $RPAT$ represents the patents authorized. β_1 and β_2 represent the depreciation rate and diffusion rate, and have the value of 36% and 3%, respectively (Popp, 2002). This paper regards the renewable energy knowledge stock as the proxy $RETI$ level. China's patent data has been available since 1985. Therefore, this paper takes 1985 as the base year to calculate the renewable energy knowledge stock. Renewable energy includes hydropower, wind power, solar energy, etc. This article searches them according to the latest International Patent Classification (IPC) codes. The relevant patent classification number is shown in Appendix A. We collect the raw data from the Patent Search System of the State Intellectual Property Office of China.[2] These patents include invention patent, design patent, and utility model patent, and are registered in China.

3.2.2. Carbon emissions (CO_2)

China has become the world largest CO_2 emitter since 2006 (Zhang et al., 2017b; Yao et al., 2018; Tian et al., 2019). High CO_2 emissions have forced China to make some commitments and take some actions to reduce emissions. Developing renewable energy is one of the efficient ways to reduce CO_2 emissions. Each of China's provinces will take measures to reduce CO_2 emission under the pressure of the central government, and developing renewable energy is one of the desirable choices. Therefore, CO_2 emission may be an important factor influencing $RETI$. This paper mainly explores whether CO_2 emission promotes the progress of $RETI$, in other words, whether $RETI$ responds to climate change. The detailed calculation method of Chinese provincial CO_2 emissions can be found in Lin and Zhu (2017).

Fig. 2 shows the number of renewable energy patents and CO_2 emission during of China during 1985–2016. We observe a high positive correlation between CO_2 emissions and renewable energy patents, and both of them experienced rapid growth after 2000. However, the number of renewable energy patents decreased significantly in 2013 and 2014. The first reason is that China has experienced severe “abandonment problem”. Facing increasing greenhouse gas emissions, the Chinese government has made energetic efforts to promote renewable energy development. However, due to the inadequate support toward the power grid construction and some other reasons, China's renewable energy power generation has encountered problems that are quite challenging since 2000. The second reason is that the large production by Chinese solar manufacturers led to excess production capacity which affected the profitability of the market and caused the solar manufacturers to reduce their investment in R&D. Because renewable energy patents account for a larger proportion of total patents, the decline in R&D investment eventually resulted in the decrease in the total amount of patents.

However, in the following years, the Chinese government proposed a series of policies to solve the “abandonment problem”. This has made renewable energy consumption to gradually increase. Even though China faced the “abandonment problem”, the Chinese government still vigorously promotes the construction of renewable energy. The “Strategic action plan for energy development (2014–2020)[3]”, which was promulgated by the government in 2014 clearly stated that the proportion of non-fossil energy in primary energy consumption will increase to 15% by 2020. The announcement of this plan indicates that China will strongly support the development of renewable energy. The relevant data showed that in 2015, the installed capacity of renewable energy power generation was 480 million kW, and by 2016 it had reached 570 million kW, a growth rate of 18.75%. Therefore, the rapid development of renewable energy pushed renewable energy companies to increase R&D investment in technological innovation.

Although China's renewable energy technology, which is measured by the number of patents, has developed relatively rapidly, the differences among the provinces are obvious. Fig. 3 shows the number of renewable energy patents in different provinces of China in 2016. We observe a great difference across provinces, and the highest in Jiangsu Province is 70 times more than that of the lowest in Hainan Province. Confronted with different CO_2 emissions constraints, different provinces have placed different emphasis on renewable energy, resulting in significant differences in technological innovation. Under the circumstances that China is pressing ahead with renewable energy, understanding the reasons for these differences are significant for the sustainable development of renewable energy. Therefore, on the basis of scientific assessment of these driving factors that have led to the difference in $RETI$ level, this paper proposes some relevant suggestions which are of great significance to the implementation of development strategies in different provinces.

3.2.3. Control variables

Global warming makes the development of renewable energy imminent. The advantages of renewable energy are renewable and nonpolluting. This is not only conducive for improving energy security and environmental quality but also key to economic development (Aized et al., 2018; Narayan and Doytch, 2017). However, due to the high cost of developing renewable energy, in addition to the external impetus of environmental and resource pressures, $RETI$ is mainly promoted by a large number of funds from governments and enterprises in the short term. Referring to previous researches, this article mainly considers the following driving factors:

(1) Enterprise R&D investment (INV). $RETI$ requires large amounts of capital investment. Technological innovation is an important way to increase competitiveness and plays a decisive role in the long-term development for enterprises (Yang et al., 2017). Since there is no renewable energy R&D investment data, Xu and Lin (2018b) regarded the R&D investment as technological progress and analyzed its effect on the development of new energy. Following Xu and Lin (2018b), this paper uses the R&D investment of industrial enterprises above designated scale as the indicator of INV. The data comes from the China Statistical Yearbook.
(2) Fiscal spending on science and technology expenditure (GTE). GTE can reflect the economic development of a region and is another important source of funding for promoting technological innovation. Compared with the enterprise R&D investment, GTE involves a

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

[3] http://www.nea.gov.cn/2014-12/03/c_133830458.htm.

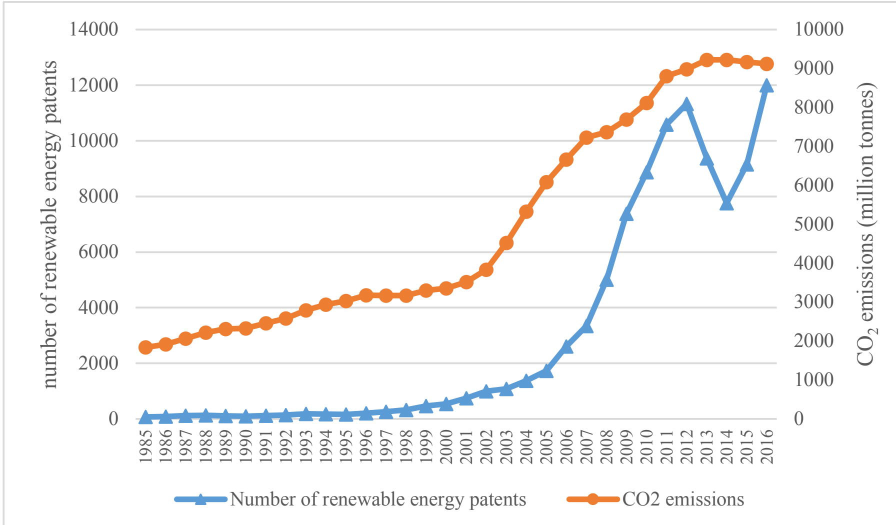

Fig. 2. Number of renewable energy patents and CO_2 emission of China. Data source: The number of patents are collected from PSA system, and the CO2 emissions data are from BP statistical review of world energy 2017 (BP, 2017)..

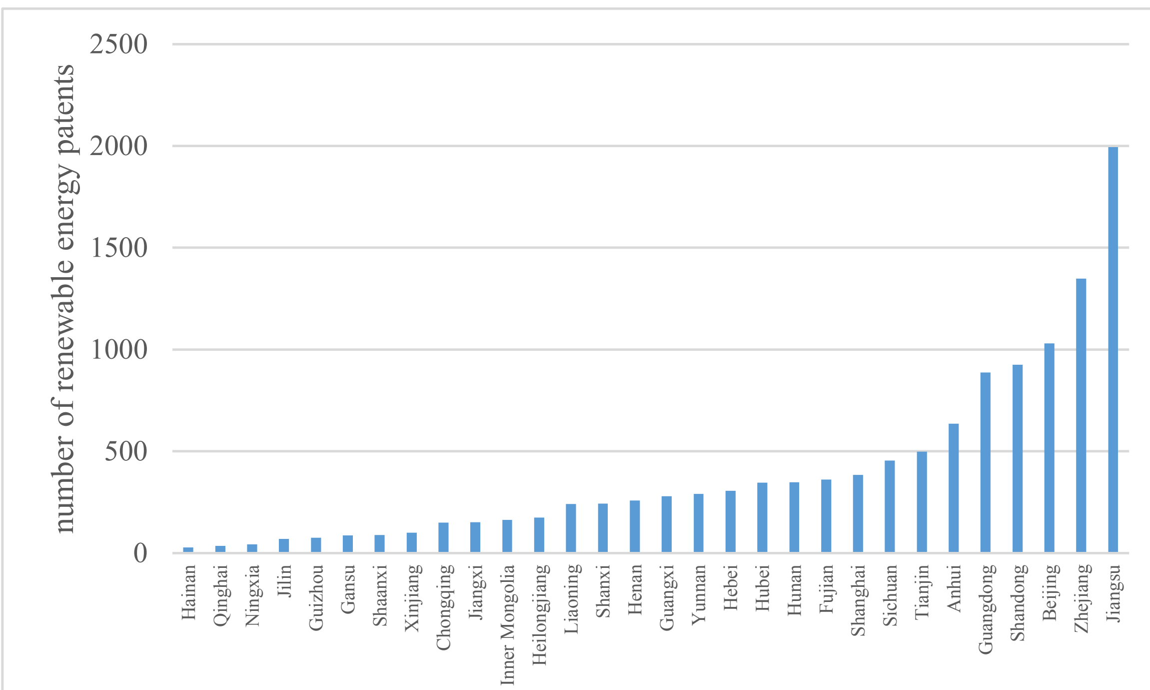

Fig. 3. Number of renewable energy patents in different provinces of China in 2016. Data source: The number of patents are collected from PSA system.

wide range, not only including basic research and applied research, but also involving scientific and technological services and exchanges. *GTE* plays an important role in solving market externalities which can affect the transformation of science and technology achievements and promotion of the development of *RETI* (Yu et al., 2016). This paper uses the local fiscal expenditure on science and technology expenditures to represent *GTE*, the data is collected from the Wind database.[4]

(3) Energy Price (*PRI*). Since renewable energy has a relatively higher cost than traditional fossil fuels, a relatively lower energy prices will make renewable energy companies to reduce the R&D investment in renewable energy due to the fact that they cannot earn sufficient profits. Therefore, lower energy prices are harmful to the technological progress of renewable energy. Furthermore, as the largest oil importing country, the price fluctuation of traditional fossil energy is harmful to maintain a stable economic growth, this has also compelled the Chinese government to develop renewable energy. Therefore, the fluctuation of energy price can affect the development of renewable energy (Atalla et al., 2017). Following the prior studies, we use the fossil fuel price inflation index as the proxy of energy price, and the data is from the China Statistical Yearbook.

(4) Energy consumption structure (*ENS*). China's energy endowment, which is characterized by “rich coal, low oil, and low gas” determines the coal-dominated energy consumption structure. Considering that the renewable energy industry is a capital-

[4] The Wind database is an authoritative Chinese economics database (http://www.wind.com.cn/).

intensive industry and requires large amounts of capital to support R&D research, renewable energy industry costs higher than the traditional fossil energy industry. Therefore, *ENS* may be harmful to technological innovation of the renewable industry. However, in the long term, the burning of fossil fuels has made China face serious environmental problems and enormous challenges in energy security. The pressure from energy conservation and emission reduction has prompted the government to develop renewable energy. We hence consider the effect of *ENS* on *RETI*. The *ENS* is represented by the proportion of the coal consumption in total energy consumption, and the relevant data is from China Energy Statistics Yearbook.

(5) Dependence on foreign energy (*DEP*). Dependence on foreign energy reflects energy supply capability. A higher *DEP* means a lower energy supply capability, which is detrimental to energy security (Radovanović et al., 2016). Stable economic growth requires a stable energy supply capability. The development of renewable energy can improve energy supply capability when facing increasingly severe environmental and resource constraints. We hence control the *DEP* and it is measured as the proportion of energy import in the sum of energy import and domestic energy production. The relevant data is from China Energy Statistics Yearbook.

GTE, INV, and *PRI* are normalized to 2000 constant price. Due to the data limitation, this paper uses the panel data of China's 30 provinces during 2000–2015, Tibet, Hong Kong, Macao and Taiwan are not included in our analysis. The descriptive statistics of all variables are presented in Table 1.

Based on the above data description and equation (2), we construct the econometric model for the determinants of *RETI*. In order to avoid possible heteroscedasticity, all data are in natural logarithm forms. The dynamic panel data model cam be specified as follows:

$$\ln RETI_{it} = \beta_0 + \alpha \ln RETI_{i,t-1} + \beta_1 \ln CO_{2,it} + \beta_2 \ln INV_{it} + \beta_3 \ln GTE_{it} + \beta_4 \ln PRI_{it} + \beta_5 \ln ENS_{it} + \beta_6 \ln DEP_{it} + v_i + u_t + \varepsilon_{it} \tag{4}$$

4. Empirical analysis

4.1. Panel unit root test

Before executing the panel co-integration test, we need to test the stability of all the variables. The panel unit root test mainly includes two types. The first assumes all panels have the same autoregressive parameter, and the most widely used is the LLC test, proposed by Levin et al. (2002). The second relaxes the assumption and assumes that different panels have its own autoregressive parameter, and this includes the IPS test (Im et al., 2003) and Fisher-type tests. We do not apply the Fisher-type tests because these tests assume that the time period T is infinite. For comparison, this paper uses the LLC test and IPS test with the null hypothesis that there is a unit root. The results are presented in Table 2. Most of the variables are non-stationary at level. However, the tests for the first difference term reject the null hypothesis for all the variables. We hence determine that all the variables are integrated of order one.

Table 1
Descriptive statistics.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
RETI	–	480	187.832	321.836	0.267	2457.870
CO_2	million tonnes	480	267.775	216.812	7.508	1112.481
INV	100 million Yuan	480	137.333	233.653	0.070	1520.550
GTE	100 million Yuan	480	33.395	56.759	0.192	442.907
ENS	%	480	64.949	17.924	12.145	99.300
PRI	–	480	177.560	57.271	93.6734	313.939
DEP	%	480	23.279	21.673	0.003	99.560

4.2. Panel co-integration test

Engle-Granger (1987) proposed the co-integration test and argued that if there is a long-run equilibrium relationship among these variables with integrated I(1), then these variables are co-integrated. Pedroni (1999, 2004) extended this idea to panel data and put forward several tests by considering the heterogeneous intercepts and trend. The null hypothesis of the Pedroni co-integration test is that there is no co-integration, with two alternative hypotheses, namely, the homogenous alternative hypothesis and the heterogeneous alternative hypothesis, which is called Within-dimension test and Between-dimension test respectively. The results of the Pedroni co-integration test are reported in Table 3. The Within-dimension test (Panel PP-Statistic and Panel ADF-Statistic) and Between-dimension test (Group PP-Statistic and Group ADF-Statistic) both reject the null hypothesis at 1% significance level, implying the existence of co-integration relationship among *RETI*, CO_2 emissions, and other factors. For a robustness test, we also construct the Kao test (Kao, 1999), and the results further confirm that there is the co-integration relationship among these variables.

4.3. Panel causality test

Before we estimate the panel regression model, we further adopt the panel causality test to explore the relationship among *RETI*, CO_2 emissions, and other driving factors. The Dumitrescu Hurlin panel causality test, which is proposed by Dumitrescu and Hurlin (2012) considers the heterogeneous characteristic for different panels, and has been proven to have good properties in the small sample. We adopt this method and the results are reported in Table 4. The results indicated that there is a bidirectional causal relationship between CO_2 emissions and *RETI*, meaning that the CO_2 emissions is an important factor in promoting the diffusion of *RETI*, beside *RETI* having a significant effect on CO_2 emissions. The causality tests also confirm that there is causality from *INV* and *GRD* to *RETI*.

4.4. Dynamic panel regression model

4.4.1. Main analysis

Based on equation (4), the system GMM estimator is adopted in the main estimation to quantitatively analyze the driving factors of *RETI*. Because the development of renewable technological innovation will affect the CO_2 emissions as well as energy structure, we regard these two variables as the endogenous variables and use the lag term of these two variables as the instruments. We adopt the stepwise regression method and the results are reported in Table 5. The coefficients of $lnCO_2$ and the lag term of *lnRETI* are significant in all cases. The *AR(2)* test cannot reject the null hypothesis even at the 10% significance level, indicating that there is no second-order correlation. Moreover, the *Hansen tests* suggest that the instruments applied here are reasonable. In summary, these two tests indicate that the regression results are reliable.

We can observe in Table 5 (model (1)–(5)), the coefficient of $lnRETI_{t-1}$ is positive and statistically significant, implying that the technological level has path-dependence and the existing technological stock will promote the development of new technologies. This is in line with reality. In addition, the results show that CO_2 emissions have a significant and positive coefficient in all cases, indicating that the regions with higher CO_2 emissions tend to make more progress in *RETI*. Presently, China has set stricter targets for CO_2 emissions reduction, and each province has also set its own CO_2 reduction targets. The provinces with higher CO_2 emissions will increase their investment in R&D research and accelerate the construction of renewable energy, which is conducive for the promotion of technological progress in renewable energy. Therefore, the positive correlation between CO_2

Table 2
Panel unit root test.

	Series	IPS Test (Wt-bar)		LLC Test (Adjusted t*)	
		Constant	Trend and constant	Constant	Trend and constant
Levels	*lnRETI*	−0.3553	−0.0664	−7.3482***	−3.9717***
	lnCO₂	−4.1558***	8.1576	−11.2122***	1.5097
	lnPRI	−4.8307***	−6.8478***	−6.0434***	−10.1503***
	lnINV	2.2462	−5.5504***	−3.0817***	−10.5468***
	lnGRD	5.2149	1.3814	−1.4888*	2.8404***
	lnENS	0.8480	2.0822	0.0903	−7.0230***
	lnDEP	−5.4404***	−7.6408***	−6.8379***	−12.4518***
First difference	*D.lnRETI*	−14.5165***	−12.3721***	−17.5239***	−16.9603***
	D.lnCO₂	−4.1877***	−8.9412***	−5.9927***	−14.3418***
	D.lnPPI	−25.1063***	−18.3111***	−29.0887***	−21.2705***
	D.lnINV	−14.3061***	−10.0200***	−19.4322***	−16.6874***
	D.lnGRD	−11.4488***	−7.2611***	−16.2404***	−14.2489***
	D.lnENS	−14.6992***	−13.0183***	−19.2384***	−18.7625***
	D.lnDEP	−21.9610***	−19.5912***	−25.1566***	−24.5090***

Note: Lag length selection based on AIC criterion; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 3
Pedroni residual co-integration test.

Within-dimension					Between-dimension		
	Statistic	Prob.	Weighted Statistic	Prob.		Statistic	Prob.
Panel v-Statistic	−4.110	1.000	−5.094	1.000	Group rho-Statistic	8.609	1.000
Panel rho-Statistic	5.395	1.000	6.606	1.000	Group PP-Statistic	−10.352	0.000
Panel PP-Statistic	−10.291	0.000	−6.718	0.000	Group ADF-Statistic	−4.494	0.000
Panel ADF-Statistic	−8.910	0.000	−5.251	0.000			

Note: Lag length selection based on AIC criterion with intercept and trend; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 4
Panel causality tests.

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
lnCO₂ does not homogeneously cause *lnRETI*	6.285	13.997	0.000
lnRETI does not homogeneously cause *lnCO2*	2.951	4.820	0.000
lnINV does not homogeneously cause *lnRETI*	2.995	4.940	0.000
lnRETI does not homogeneously cause *lnINV*	3.649	6.741	0.000
lnGTE does not homogeneously cause *lnRETI*	7.232	16.602	0.000
lnRETI does not homogeneously cause *lnGTE*	3.056	5.108	0.000
lnENS does not homogeneously cause *lnRETI*	1.474	0.754	0.451
lnRETI does not homogeneously cause *lnENS*	2.498	3.573	0.000
lnPRI does not homogeneously cause *lnRETI*	0.802	−1.095	0.273
lnRETI does not homogeneously cause *lnPRI*	2.400	3.302	0.001
lnDEP does not homogeneously cause *lnRETI*	1.218	0.050	0.960
lnRETI does not homogeneously cause *lnDEP*	3.348	5.911	0.000

emissions and *RETI* is in line with our expectation, and this confirms that innovation in renewable energy technologies responds actively to climate change.

Our results also suggest that *lnGTE* and *lnINV* are positively correlated with *lnRETI*, showing that the investment in R&D from governments and enterprises all can promote *RETI*. Prior studies suggested that R&D from governments and enterprises all have a positive impact on technological progress (Kang et al., 2018; Lin and Chen, 2019). By comparison, the coefficient of *lnGTE* is significantly greater than that of *lnINV*. This indicates that the government's support plays a key role in the development of *RETI*. The energy consumption structure, which is measured as the proportion of coal consumption (*lnENS*) is significant with a negative sign (Xu and Lin, 2018b). This result can be explained that the coal-dominated energy structure will inhibit the development of *RETI*.

We gradually add *PRI* and *DEP* to the estimation process. The results show that the coefficient of energy prices is not significant in all cases, indicating that the current energy prices cannot promote the development of innovation in renewable energy technologies. Prior studies

Table 5
Main estimation results.

Dependent variable: *lnRETI*	(1)	(2)	(3)	(4)	(5)
lnRETI$_{t-1}$	0.552***	0.512***	0.521***	0.431***	0.428***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnCO₂	0.826***	0.613***	0.502***	0.469***	0.474***
	(0.000)	(0.000)	(0.003)	(0.003)	(0.008)
lnENS	−1.307***	−1.247***	−1.190***	−1.067***	−1.016***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnINV		0.138***	0.156***	0.117***	0.113***
		(0.001)	(0.001)	(0.001)	(0.001)
lnPRI			0.100	−0.249	−0.255
			(0.519)	(0.199)	(0.182)
lnGTE				0.206***	0.204***
				(0.000)	(0.000)
lnDEP					0.039
					(0.329)
Constant	3.038**	3.562***	3.289**	4.760***	4.474***
	(0.047)	(0.000)	(0.018)	(0.000)	(0.001)
AR(1)	−2.659	−2.712	−2.659	−2.775	−2.775
	(0.008)	(0.007)	(0.008)	(0.006)	(0.006)
AR(2)	1.183	1.158	1.128	1.203	1.210
	(0.237)	(0.247)	(0.259)	(0.229)	(0.226)
Hansen test	28.803	27.681	27.128	27.967	28.204
	(0.999)	(1.000)	(1.000)	(1.000)	(1.000)

Note: (1) *p*-values in parentheses; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
(2) *lnCO₂* and *lnENS* are treated as the endogenous variables and the instruments are selected by using the collapse sub-option, the robust standard error estimates are used in the regression process.
(3) The *Hansen test* is used to test the validity of instrument variables (over-identification restriction). Different from the *Sargan test*, the *Hansen test* is efficiency under heteroscedasticity condition. By checking, the data we adopted in this paper satisfy the heteroscedasticity condition, thus, the robust standard error estimates are used in the regression process and we adopt the *Hansen test.*.

Table 6
Robustness test.

Dependent variable: *lnRPAT*	(1)	(2)	(3)	(4)	(5)
$lnRPAT_{t-1}$	0.567***	0.520***	0.588***	0.471***	0.471***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$lnCO_2$	0.796***	0.664***	0.420***	0.440***	0.461***
	(0.000)	(0.000)	(0.002)	(0.005)	(0.001)
lnENS	−1.136***	−1.071***	−0.961***	−0.958***	−0.898***
	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)
lnINV		0.112**	0.142***	0.101***	0.091**
		(0.017)	(0.002)	(0.003)	(0.011)
lnPRI			0.045	−0.256	−0.243
			(0.731)	(0.166)	(0.190)
lnGTE				0.196***	0.184***
				(0.003)	(0.003)
lnDEP					0.058
					(0.184)
Constant	2.399*	2.584**	2.800*	4.376***	3.855***
	(0.095)	(0.012)	(0.092)	(0.000)	(0.001)
AR(1)	−2.902	−3.018	−3.057	−2.968	−3.063
	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)
AR(2)	0.760	0.741	0.759	0.755	0.804
	(0.447)	(0.458)	(0.448)	(0.450)	(0.422)
Hansen test	28.855	27.794	29.089	27.663	28.448
	(0.999)	(1.000)	(0.999)	(1.000)	(0.999)

Note: (1) *p*-values in parentheses; $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
(2)$lnCO_2$ and *lnENS* are treated as the endogenous variables and the instruments are selected by using the collapse sub-option, the robust standard error estimates are used in the regression process.

revealed that higher energy price has an “induced effect” on promoting the progress of *RETI* due to the relatively high cost of renewable energy (Ley et al., 2016; Kruse and Wetzel, 2015). However, the strict governmental control leads to the distortion in China's energy pricing system to some extent, resulting in lower energy prices (Ju et al., 2017; Li and Lin, 2018). Even though a lower energy price is beneficial for economic growth, it cannot truly reflect the market value. As a result, it will hinder the progress of technological innovation as well as energy transition. Therefore, the insignificant correlation between *lnPRI* and *lnRETI* is in line with China's actual situation. The results of the model (5) also show that there is a positive correlation between *lnDEP* and *lnRETI* which indicates that the higher dependence on foreign energy is beneficial for developing renewable energy technologies but the impact is not significant.

4.4.2. Robustness test

In order to verify the robustness of the relationship among *RETI*, CO_2 emissions and other driving factors, this paper conducts robustness test. We continue adopt the system GMM method. We replace the *lnRETI* by directly using renewable energy patents (*lnRPAT*) for the robustness test. We use the stepwise regression method and the regression results are shown in Table 6. The *AR(2)* test and *Hansen test* both show that the model is reasonable. The results of the robustness test further verify that there is a significantly positive correlation between CO_2 emissions and *lnRPAT*. The signs and significance levels of other variables are similar to the results in Table 6, which indicates that the main estimation results are robust.

5. Conclusion and policy implication

The development of renewable energy plays an important role in China's energy security, energy independence and climate mitigation (Tsai and Chou, 2005; Wang et. Al., 2018). Technological innovation is a determinant factor in renewable energy development. An in-depth analysis of the drivers affecting innovation in renewable energy technological innovation is crucial for China's energy transition.

Based on China's provincial panel data from 2000 to 2015 and panel data techniques, this paper explores the response of renewable energy technological innovation respond to climate change, and further analyzes the driving factors such as energy price and innovation input on this innovation process. The reliability of the results is verified by a robustness test. The main conclusions are as follows: (1) Even though there is rapid progress in China's renewable energy technologies in recent years, there are great differences in innovation level across China's provinces. (2) There is a bidirectional relationship between CO_2 emissions and innovation level., indicating that extensive CO_2 emissions have promoted renewable energy technological innovation. (3) R &D investment from government and enterprise is conducive for promoting the innovation level. (4) Energy price has an insignificant effect on innovation in renewable energy technologies and we attribute this to the unreasonable energy price mechanism. Regional differences in renewable energy technologies are detrimental to the sustainable development of renewable energy. In order to promote China's innovation level as well as increase the contribution of renewable energy to China's low-carbon economic and social development, this paper proposes the following policy recommendations.

On the one hand, the government should guide and support enterprises for technological innovation and increase the scale of technology expenditures. The positive impact of CO_2 emissions on technological innovation indicates that renewable energy technologies respond actively to climate change. The policy implication is that we need to notice the role of innovation in renewable energy technologies on CO_2 reductions and funding support is necessary to further promote innovation level. This paper reveals that innovation investment (including enterprises' R&D investment and fiscal spending on science and technology) has a significant role in promoting innovation level, but they play different roles. Technological innovation is an important way for enterprises to increase their competitiveness, but they often face high risk, high cost and uncertainty problems during the innovation process. As a result, the innovation investment from enterprises is always lower than the socially optimal level. As the main promoter of national innovation, the government can optimize technological innovation level through technology expenditures and other policy instruments including government subsidies, investment in R&D projects and indirect measures such as tax incentives. In other words, the main role of fiscal spending on science and technology is to solve the problems existing in the R&D research process which cannot be effectively solved by the market resources allocation. Thus, the government should give full play to the guidance of enterprise and support for renewable energy technological innovation and meanwhile increase the investment in science and technology especially paying attention to the application effect of R&D fund in these provinces with higher CO_2 emissions and lower innovation level, and eventually narrow the technology gap among different regions.

On the other hand, there is a need to gradually rationalize the role of the energy price mechanism in promoting technological innovation. Technological innovation is an important factor to promote the development of renewable energy. It is particularly important to promote the innovation level on the premise of China's vigorous development of renewable energy. The low price of traditional fossil fuels and China's coal-dominated energy endowment have caused China to consume large amounts of coal. This phenomenon is not only harmful to China's low-carbon development but also will inhibit the technological progress of renewable energy (Xu and Lin, 2018a). Therefore, the Chinese government should give full play to the role of the energy price mechanism, impose a tax on traditional fossil fuels, and provide certain subsidies for renewable energy. It is also necessary to gradually straighten out the role of the energy price mechanism, increase the market competitiveness of renewable energy and further promote technological progress.

In closing, it should be noted that this paper is a preliminary discussion to reveal the role of innovation on climate change, much remains to be done. On the one hand, more accurate data are needed to reveal the true technological innovation level. On the other hand, a systematic model is needed to integrate technological innovation into the energy system so as to deeply analyze the impact of technological innovation on climate change.

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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 et al. (2010), Johnstone and Haščič (2010).

Conflicts of interest

Declarations of interest: none.

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