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RESEARCH ARTICLE

Exploring the spatial pattern of renewable energy technology innovation: evidence from China

Zhengxia He[1] · **Leyi Kuai**[2] · **Xin Chen**[3] · **Wenxing Shen**[4] · **Wenbo Li**[2]

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Abstract

Considering the obvious regional differences in China, research on the drivers for renewable energy technology innovation (RETI) needs to fully consider the spatial factors. Based on the expanded function of knowledge production, which includes the human capital, institutional quality, and industrial scale, and using panel data from 29 provinces during 2006–2017, this study examines the factors promoting RETI by employing spatial regression methods. The results show that RETI presents moderate spatial agglomeration and spatial heterogeneity. Human capital, enterprise R&D intensity, and research institution R&D intensity have a significant driving effect on the local RETI, and the university R&D intensity, institutional quality, and industrial scale have no significant contribution. Human capital is the most important factor driving the local RETI, and enterprise R&D intensity has the strongest spatial spillover effect on the RETI of the surrounding provinces. In addition, the R&D intensity of enterprises and research institutions can enhance the local RETI and also significantly promote RETI in surrounding provinces through the spatial spillover effect. In contrast, human capital has played a significant driving role in the local RETI, whereas its spatial spillover effect on the surrounding provinces is not obvious. Therefore, the direct and spatial spillover effects of enterprise R&D intensity and research institution R&D intensity should be fully considered in policy making. In addition, effective policies should be formulated to break the block division of human capital investment and to promote the optimized allocation of talented people in order to better promote RETI in China.

Keywords Renewable energy technology innovation · Spatial pattern · Spatial spillover · Spatial Durbin model

Abbreviations

RETI	Renewable energy technology innovation
R&D	Research and development
IURC	Industry-university-research cooperation
FYP	Five-year-plan
SDM	Spatial Durbin model
OLS	Ordinary least squares
IPC	The International Patent Classification
WIPO	The World Intellectual Property Organization
REL	Renewable Energy Law
GDP	Gross domestic product

Introduction

Actively developing the renewable energy industry and realizing the low-carbon transformation of the energy system is the key to enhancing national energy security and solving the contradiction between energy consumption and greenhouse gas reduction (Dai et al. 2016). Over 90% of the countries signing Paris Agreement have determined specific targets for renewable energy development. China has set a goal of reaching the peak for CO2 emissions and 20% renewable energy in its power supply by 2030. In contrast, the European Union has set a target for renewable energy to account for 35% of its power supply. Currently, the scale of China's renewable energy industry makes it the highest-ranked in

Responsible Editor: Roula Inglesi-Lotz

✉ Xin Chen
1066959425@qq.com

Zhengxia He
hezhengxia79@163.com

[1] School of Economics, Hangzhou Normal University, Hangzhou 311121, China

[2] Business School, Jiangsu Normal University, Xuzhou 221116, China

[3] Business School, University of Shanghai for Science & Technology, Shanghai 200093, China

[4] College of Economics and Management, Nanjing Forestry University, Nanjing 210037, China

the world,[1] but its large-scale development still faces a series of problems such as its high cost and difficult consumption. Renewable energy technology innovation (RETI) can reduce utilization cost, solve some problems of renewable energy integration and consumption, and improve the competitive edge of the industry. However, China's RETI as a whole is still in the stage of creative imitation, so actively promoting independent innovation is the key to obtaining a competitive advantage and achieving large-scale development.

Innovation is more likely to happen in a place adjacent to the source of the relevant inventions. Previous studies have proved that the knowledge creation process of renewable energy has an obvious spatial association (Miremadi et al. 2019; Shahnazi and Shabani 2020; Khezri et al. 2021); that is, the farther the geographical distance, the lower the probability of knowledge flows (Verdolini and Galeotti 2011). Thus, RETI presents significant spatial agglomeration and spatial spillover effects. Therefore, by employing panel data from twenty-nine Chinese provinces, this study intends to adopt a spatial econometric model to deeply explore the factors enhancing RETI.

In addition, according to the report in the *Global Renewable Energy Investment Trends in 2019*, from 2010 to 2019, China was the largest investor in installed renewable energy capacity worldwide in this decade with a total investment of 758 billion US dollars.[2] In aspects of R&D investment in renewable energy, after the issuance of the *Renewable Energy Law (REL)* in 2005, there has been significant expansion in renewable energy development in China. The Ministry of Science and Technology has given priority to deploying technology R&D in renewable energy. By the end of 2015, over 2.3 billion yuan had been invested in renewable energy technologies. Over the course of the 13th Five-Year-Plan, the central government plans to invest 700 million yuan in the implementation of two key R&D projects: "renewable energy and hydrogen energy technology" and "smart grid technology and equipment."[3] The progress of renewable energy technology depends on the comprehensive effect of research institutions, universities, enterprises, human capital, markets, and policies. Therefore, it is meaningful and critical to examine the key drivers for RETI and explain their relative effect; this can provide useful policy enlightenment and improve the pertinence of the policy.

This study intends to contribute to this field in the following respects. (1) On the basis of the original knowledge production function, it introduces human capital, a marketization indicator, and industrial scale to analyze the relative efficacy of the various drivers of RETI. (2) From the spatial perspective, it is a new attempt to investigate the spatial spillover impact of different factors on RETI. The renewable energy market in China is very promising, and the proposed carbon peak and carbon neutral targets also provide a new opportunity for the development of renewable energy. And at present, there are few papers that study the spatial pattern of renewable energy technology innovation from the Chinese perspective. Therefore, it is of practical significance to explore the renewable energy technology innovation in China from the spatial perspective.

After the introduction, this study summarizes the related literature in "Review of relevant literature" section. The research methods presented in "Methodology" section give the research design, which includes the model specifications, data sources, and description. "Results" section presents the empirical results, while the deep discussion about these results is given in "Discussion" section. The conclusions are presented in "Conclusions and policy recommendations" section and are accompanied by some policy recommendations.

Review of relevant literature

Impact of R&D investment on innovation

The knowledge production function proposed by Griliches (1979, 1986) regards R&D investment as the main input for innovation, and many empirical studies have found that the knowledge production function is a good statistical model in technological innovation research (Anselin et al. 1997; Bode 2004).

In the field of renewable energy, the existing research shows that public R&D investment will promote RETI (Nemet 2009; Kim and Kim 2015). Specifically, the key reason for the government's intervention through public R&D investment is market failure and uncertainty in the process of RETI (Jacobsson and Johnson 2000); thus, public R&D investment can effectively narrow the gap caused by insufficient private investment (Koseoglu et al. 2013). Some recent studies have asserted that public and enterprise R&D investment are conducive to improving RETI (Lin and Zhu 2019). Some researchers believe that public R&D investment will

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[1] By 2018, China's main renewable energy sources, including hydropower, wind, and solar power, have been ranked the first worldwide in aspects of new and cumulative installed capacity. In China's total energy consumption, the proportion of renewable energy has been continually increasing, and the energy structure adjustment continues to accelerate. In 2018, the generating installed capacity of renewable energy represented 38.4% of the aggregate installed capacity, the generated capacity represented 26.7% in the aggregate generated capacity, and the share of the primary energy consumption increased to 12.4%. China's clean and low-carbon green energy system has taken shape.

[2] Global Renewable Energy Investment Trends in 2019.

[3] www.people.cn. China has invested more than 3 billion yuan in renewable energy technology R&D. http://env.people.com.cn/n1/2019/1225/c1010-31521520.html.

crowd out enterprise R&D investment (Yu et al. 2016), but others think that public R&D investment will encourage enterprise R&D investment (Miremadi et al. 2019). Further research shows that some background factors (such as industry characteristics and national characteristics) can moderate the relationship between government subsidies and enterprise R&D investment (Görg and Strobl 2007).

From the specific mechanism of public R&D support (such as public R&D subsidies) affecting renewable energy production scale and technological innovation, empirical studies in some countries with relatively advanced renewable energy technology development showed that, the knowledge spatial spillover between regions brought by public R&D support helps to promote the production and technological innovation of renewable energy (Miremadi et al., 2019). In addition, public R&D subsidies have a significant positive impact on innovation at the enterprise, industry, and national levels. For enterprises with technological innovation subjects, public R&D subsidies promote the improvement of their innovation capability through internal and external organizational learning.

The conceptual framework analyzing the geographical spillover in university research originated from Griliches (1979), who assumes that the knowledge spillover from university research is the main source for the knowledge production of the high-tech sector. Many researchers confirm that R&D cooperation among industry, universities, and research institutions has significant positive impacts on innovation (Siegel et al. 2003; Liefner et al. 2006). However, industry-university-research cooperation (IURC) still faces a series of difficulties, such as technical uncertainty, information asymmetry, high knowledge transaction costs, and the need for absorptive capacity (Cassiman and Veugelers 2002). Some other studies believe that R&D cooperation between enterprises and universities is closely related to the industrial characteristics and enterprise characteristics, such as the R&D intensity, enterprise scale, and whether it is easy to obtain public R&D funding (Carboni 2013).

Impact of human capital on innovation

The theoretical basis of human capital as an important driving force of innovation is the knowledge spillover mechanism based on the talent flow, especially tacit knowledge spillover. Talent flows in different spaces and interactions with the surrounding groups. This not only promotes new knowledge creation, it also accelerates the knowledge spread among different groups (Almeida and Kogut 1999). Knowledge spillover based on talent flow is greatly influenced by the quality of the human capital (Audretsch and Feldman 2004). Thus, the knowledge spillover mechanism based on talent flow shows that innovation depends not only on the total amount of human capital, but also on the rational allocation, flow, and quality of the human capital.

Some researchers have discussed the theoretical mechanism of human capital to technological innovation from the perspective of the economic growth theory (Romer 1990). Tong et al. (2008) pointed out that human capital has effects on technological innovation through the ability to acquire knowledge, knowledge digestion, knowledge transformation, and knowledge utilization. Zhang and Wu et al. (2019) regard the upgrading of the human capital structure as the index of the quality of the human capital, and believe that the way that the upgrading of the human capital structure affects industrial innovation includes the saving of the industrial innovation input and the growth of the industrial innovation output.

Empirical researchers have not come to the same conclusions. Some research shows that human capital plays a significant driving role in technological innovation (Banerjee and Roy 2014; Zhang and Yang 2019), but others show that the effect of human capital on technological innovation is not significant (Fan and Li 2014; Danquah and Amankwah-Amoah 2017). However, other studies have pointed out that there is a negative correlation between human capital and technological innovation (Yan and Wang 2004).

Impact of institutional quality on innovation

Some scholars have explored the direct role of institutional quality in promoting innovation (Wu et al. 2015). Wu et al. (2019) examined the different effects of the institutional environment (including market maturity, intellectual property protection, and cultural distance) in the host country on enterprise innovation. Research shows that the absorptive capacity of enterprises moderates on the role of institutional contexts in innovation. Some studies have investigated the theoretical mechanism of the institutional contexts on innovation. Schøtt and Jensen (2016) believed that the institutional environment would enhance the role of the enterprise network in promoting innovation.

Some empirical researchers have explored how the institutional quality moderates between different elements and innovation, such as foreign direct investment (FDI) (Qu et al. 2015), intensity of R&D (Yi et al. 2017), and human capital (Barasa et al. 2017). Remarkably, believed that institutional quality negatively moderates the FDI spillovers of innovation in high-tech industries. Employing the data from Chinese manufacturing enterprises, Yi et al. (2017) showed that the state-owned institutions have moderated positively between the R&D intensity and innovation. Barasa et al. (2017) showed that regional institutional quality has positively moderated between enterprise resources and innovation. However, Bianchini et al. (2019) evaluated how the public R&D subsidy policy influences innovation under different institutional frameworks and showed that regional institutional quality only moderates insignificantly between public R&D subsidies and innovation.

Market liberalization is an important aspect of institutional quality. Some researchers have focused on the influence of market liberalization (i.e., the degree of market competition) on enterprise innovation (Chen 2017). Currently, there is no consensus about the impact of market competition on innovation. One view is that product market competition reduces the excess profits of enterprises and increases imitation among enterprises, which is not conducive to enterprise innovation (Grossman and Helpman 1991). The opposite view is that product market competition will improve market efficiency, and enterprises can obtain strategic effects and first mover advantages through innovation (Boone 2001). In addition, Aghion et al. (2005) confirmed the inverted U-shaped relationship between product market competition and enterprise innovation. Meanwhile, the influence of competition on innovation is moderated by the specific characteristics of technology. In general, the positive effect of competition on innovation is expected to dominate in the context of radically innovative technologies. Renewable energy innovation is a fundamental and radical transformation to the mode of energy centralized production, so market liberalization positively influences renewable energy innovation (Jacobsson and Bergek 2004; Makard and Truffer 2006).

Impact of comprehensive driving factors on innovation

Many studies use traditional econometric methods to explore the comprehensive driving factors for renewable energy innovation, such as the state policy, resource availability, technology cost, public acceptance (Doris et al. 2009), economic growth (Destek and Aslan 2017), export trade, and fossil energy price (Amri 2017). This kind of research mainly uses traditional econometric methods and does not take the spatial effect into account. There are few studies on the spatial autocorrelation and spatial variation of the social and economic phenomena that use spatial econometric methods. Due to the vast size of China and the significant differences between the regions, Xu and Lin (2018) used the geographical weighted regression model to examine the driving factors for renewable energy R&D investment. It shows that considering the obvious heterogeneity in the economic structure, income, as well as fossil energy imports among the provinces in China, the impact of the economic growth, energy dependence on foreign countries, and technological progress on R&D investments in renewable energy is strongest in the eastern provinces, moderate in the central provinces, and weakest in the western provinces.

Research review

In the past, most scholars mainly used the traditional econometric methodologies to carry out their research on the precondition that the role of various factors on RETI in different regions is constant and independent. However, these studies often pay less attention to the spatial variability and spatial dependence of the economic phenomena (He et al. 2018; Corsatea 2016). Since the 1990s, as it is one of the important concepts to explain agglomeration, innovation, and regional economic growth, the research unit of knowledge spillover has gradually turned from enterprises to space, and more and more researchers have carried out in-depth research on industrial innovation from the perspective of regional space. Technological innovation has become the key driving force to enhance the international competitiveness of the renewable energy industry and promote the high quality and scale development of the industry. At present, there are few in-depth studies that were conducted from the perspective of space to explore the relative effect of different driving factors on RETI. Miremadi et al. (2019) studied the impact of knowledge spillovers on renewable energy development using the Nordic countries as an example. The study found that the innovation spillover process between countries can bring successful experiences to other countries and promote the development of renewable energy technology innovation in each country and globally. Shahnazi and Shabani (2020) also studied the spatial spillover effect of renewable energy production among EU countries from a national perspective and empirically confirmed the existence of spatial effects. There are also some studies based on spatial perspective in China. Bai et al. (2020) study the factors influencing the convergence of RETI in China from a spatial perspective. There are also some scholars who study the impact of renewable energy technology innovation on issues such as air pollution and industrial clean production from a spatial perspective (Zhu et al. 2020, 2021). Studies on the influencing factors of renewable energy technology innovation are still relatively few. This paper builds on these previous literatures to investigate whether there is a spatial spillover effect of renewable energy technology innovation among Chinese provinces, and expands the study of renewable energy impact factors by subdividing R&D investment into enterprise R&D intensity, research institution R&D intensity, and university R&D intensity, and introducing human capital, marketability indicators, and industry scale variables. It also provides new ideas for the study of renewable energy technology innovation in China from the perspective of spatial spillover. The goal of this study is to contribute in this regard.

Methodology

Model specification

The function of knowledge generation proposed by Griliches and Jaffe (Griliches 1979, 1986; Jaffe 1989) is adopted in this study. Its specific form is as follows:

$$K_i = RD_i^{\beta} Z_i^{\gamma} e_i \tag{1}$$

where K represents innovation output, RD represents R&D expenditure, Z represents a series of economic and social variables (such as human capital and institutional quality), e refers to a random disturbance item, and i refers to the observation unit (it refers to the province in this study). The production function proposed by Griliches-Jaffe is on the basis of the assumption that the driving effect of R&D investment in one region on patents in the same region indicates the existence of geographic media spillover. Therefore, the model is suitable for the study of industrial technological innovation activities from the spatial perspective. It is worth mentioning that the research of Anselin et al. (1997) and Bode (2004) all focus on the spatial spillover effect of innovation activities.

The logarithmic form of model 1 can be expressed as follows:

$$\ln(K_i) = \alpha + \beta \ln(RD_i) + \gamma \ln(Z_i) + e_i \tag{2}$$

where α is a constant, e_i denotes the error, and β, γ represent the coefficients of $\ln(RD_i)$ and $\ln(Z_i)$, respectively. According to the actual situation of the R&D investment in China's provinces, this study expands the R&D investment from universities and enterprises to research institutions and uses the knowledge production function to investigate the driving impact of R&D investment by provincial research institutions, universities, and enterprises on industrial innovation in China. Moreover, this study brings a series of economic and social variables, such as human capital, institutional quality, and industrial scale, to the model.

The standard form of the complete model used for our study after logarithmic treatment is as follows:

$$\begin{aligned}\ln(reti_{it}) = \alpha + \beta_1 \ln(erdi_{it}) + \beta_2 \ln(srdi_{it}) + \beta_3 \ln(urdi_{it}) + \gamma_1 \ln(hc_{it})\\ + \gamma_2 \ln(mi_{it}) + \gamma_3 \ln(reic_{it}) + e_{it}\end{aligned} \tag{3}$$

In Eq. (3), i means the region, t represents the time, and *reti* denotes the technology innovation for renewable energy, for which the count of patents application is used as a proxy. *erdi*, *srdi*, and *urdi* represent the R&D intensity of the enterprises, research institutions, and universities, respectively. *hc* denotes human capital and is measured by the total human capital at the provincial level; *mi* denotes the institutional quality and is measured by the marketization indicator[4]; and *reic* represents the industrial scale and is measured by the installed capacity of renewable energy.

Data sources and description

After the issuance of the *REL*, the Chinese renewable energy industry entered a period of rapid development. The starting point for this study is set as 2006. We obtained the data from a series of statistical yearbooks from 2007 to 2018, such as China Statistical Yearbook, China Science and Technology Statistical Yearbook, the Provincial Marketization Indicator Report of China (2018), and the human capital website of Renmin University of China, and the China Electric Power Yearbook (2007–2018). The selection criteria and sources of the specific proxy indicators for the dependent variables and explanatory variables are as follows.

According to most economic researchers, the counts of patent applications are generally regarded as the most common approximate indicator for a company's innovation performance in new technologies, processes, and products (Griliches 1990). In this study, the selection of the number of patent applications, rather than number of authorizations, is mainly because there is a long time lag between the approval of the patent office and the authorization of patent implementation, so the use of patent authorization cannot reflect the technological innovation output of each region at the correct time. In China, there are mainly three patent forms: patents for appearance design, patents for utility model, and patents for invention. Among these, patents for invention can best represent the creation of new knowledge and achievements of technological development, so it is most appropriate to choose the number of patents for invention based on the application date as the proxy indicator for technological innovation, that is, the number of patent applications for renewable energy will be used as a measurement indicator for the dependent variable: renewable energy technology innovation (RETI). By using the International Patent Classification (IPC) code[5] and combining this with

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[4] The marketization indicator is defined from five aspects: the game between the government and market, the development and perfection of the product and factor market, the development and status of the non-public economy in the market, the establishment and development of market intermediary organizations, and the laws environment. There are 18 basic indexes used, and they are constructed with principal component analysis as the basic econometric method. In order to ensure objectivity, the calculation of the basic indexes is based on the statistical data of authoritative institutions or the survey data of enterprises and does not depend on subjective factors such as the "expert score." It is a useful economic analysis tool and is used to analyze the relative relationship between the institutional reform processes in various regions.

[5] This was developed by the World Intellectual Property Organization (WIPO).

Table 1 IPC codes employed in this study

Different renewable energy sources	IPC code
Wind	F03D, B63H13/00
Solar	F03G6/00–08, F24J2, F25B27/00, F26B3/28, H01L31/042, H02N6/00, E04D13/18, B60L8/00
Geothermal	F03G4/00–06, F24J3/00–08, H02N10/00
Ocean	F03G7/05, F03G7/04, E02B9/08, F03B13, F03B7/00
Biomass	C10L5/44, F02B43/08, C10L1/14, C12P7, C10L1/02, C12M1/107

Table 2 Variables' definition

Variable	Definition	Unit of measurement
Renewable energy technology innovation (reti)	The number of patents application	piece
R&D investment intensity from enterprises (erdi)	R&D investment from enterprises divided by regional GDP	percent
R&D investment intensity from research institutions (srdi)	R&D investment from research institutions divided by regional GDP	percent
R&D investment intensity from universities (urdi)	R&D investment from universities divided by regional GDP	percent
Human capital (hc)	Total human capital at provincial level	billion yuan
Institutional quality (mi)	Marketization index	score
Industrial scale (reic)	Installed capacity of renewable energy	10 MW

the relevant literature, this study will determine the patent counts based on the application date for different renewable energy sources (mainly solar, wind, biomass, marine, and geothermal) and will then obtain the index value for RETI by summing up. Table 1 shows the relevant IPC codes used in this study.

The R&D intensity of the enterprises, research institutions, and universities in each province is obtained by calculating the proportion of the internal R&D expenditure divided by the regional GDP with the unit being percent. The data for internal R&D expenditure and regional GDP comes from the China Statistical Yearbook (2007–2018) and the China Science and Technology Statistical Yearbook (2007–2018). The provincial human capital is obtained through the human capital website of Renmin University, which is the actual total amount of the provincial human capital with the unit being one billion yuan. The marketization indicator for each province was obtained from the China Provincial Marketization Indicator Report (2018), with the unit being the score. The installed capacity of the renewable energy in each province is obtained through the China Electric Power Yearbook (2007–2018) with the unit being 10 MW. Table 2 provides the variables' definition.

This study has a panel sample of 348 observations from 29 provinces in China from 2006 to 2017. Table 3 provides the variables' descriptions.

Considering that China's renewable energy developed very rapidly after the issuance of the REL in 2005, Fig. 1 indicates the total patent counts based on the applications for the five sources of renewable energy in 2006–2017. As shown in Fig. 1, since the promulgation of the REL in 2005, the patent counts based on the application date for the five sources of renewable energy have increased dramatically. From 2006 to 2017, the highest patent counts have been for solar applications. These have been followed, in order, by biomass, wind energy, ocean energy, and geothermal energy patents. Specifically, from 2006 to 2010, the solar patent applications grew rapidly, reached their first peak in 2010, declined from 2011 to 2013, rebounded in 2014, reached their second peak in 2015, and then declined again with a large drop in 2017. In contrast, from 2006 to 2012, the biomass patent applications grew steadily, but there was a significant decline in 2013 compared with 2012, and this was followed by a slow and stable rising trend from 2014. There was a slight decline in 2017 compared with the previous year. Similarly, from 2006 to 2012, the patent applications for wind energy grew steadily but declined from 2013 to 2014 before beginning to pick up again from 2015. At the

Table 3 Variables' descriptions

Variable	Obs	Mean	Std. dev	Min	Max
reti	348	174.6	237.6	0	1317
erdi	348	1.051	0.579	0.0900	3.470
srdi	348	0.326	0.565	0.0300	3.560
urdi	348	0.147	0.144	0.0200	0.840
hc	348	8748	6142	460.0	29,119
mi	348	6.387	1.903	2.330	11.11
reic	348	309.0	549.0	0	3413

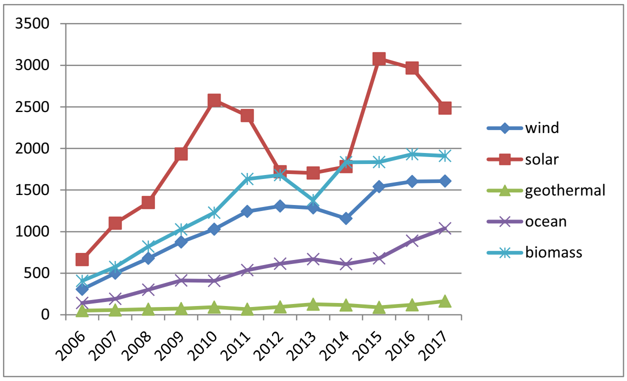

Fig. 1 Patent counts based on applications for different sources of renewable energy

same time, the patent applications for marine energy rose steadily. There have been relatively few patent applications for geothermal energy, but they are also increasing.

As shown in Fig. 2, from 2006 to 2017, China's top five provinces in renewable energy patent applications were Jiangsu, Beijing, Zhejiang, Shandong, and Guangdong. It can be seen that Jiangsu, Beijing, Zhejiang, Shandong, and Guangdong have obvious advantages over the other provinces in RETI.

Spatial econometric approaches

This part will summarize the spatial econometric method in this study. The relevant methods of spatial econometrics refer to the work of Anselin (1988) and LeSage and Pace (2009). A series of influencing factors, which include the R&D intensity of the enterprises, research institutions, and universities, as well as the human capital, that drive RETI are not independent in each province. The flow of influencing factors in one province may be affected by the economic behavior of other provinces. Therefore, ignoring their spatial association may lead to incorrect model specifications. Based on this, this study adopts spatial regression methodologies to examine the effects of various drivers on RETI.

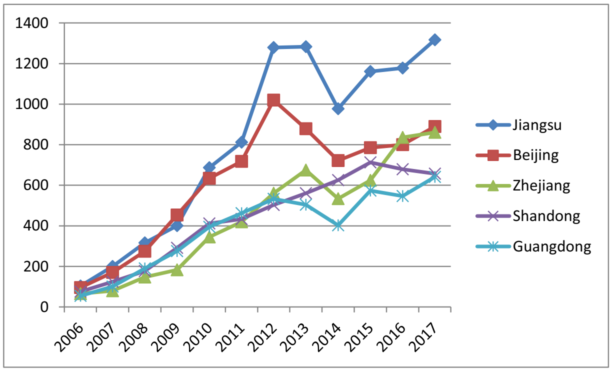

Fig. 2 China's top 5 provinces in renewable energy patent applications during 2006–2017

Spatial weights

In order to incorporate spatial interaction into the regression model, a weight matrix that can effectively express the spatial interaction is needed. The matrix for spatial weight effectively represents the spatial relationship between the units (such as provinces), that is, the "spatial structure" between the data is expressed by a quantitative method. The representation of this spatial structure is usually determined by the contiguity or distance between the spatial units. In this study, the spatial contiguity matrix (Getis 2009) is proposed to represent the spatial relationship between different provinces in China. Therefore, the form of the spatial weight matrix used in this study is shown in Eq. (4), which, in essence, takes the form of a binary contiguity matrix. It assumes that the spatial interaction will occur as long as there is a common border of non-zero length between the spatial sections. The assignment rule is that when the adjacent space units *i* and *j* share the same border, they are represented by 1, otherwise they are represented by 0.

$$\begin{gathered} W_{ij} = \begin{bmatrix} w_{11} & \dots & w_{n1} \\ \dots & w_{ij} & \dots \\ w_{1n} & \dots & w_{nn} \end{bmatrix} \\ W_{ij} = \begin{cases} 1 \ \text{if} \ i \ \text{and} \ j \ \text{share the same border} \\ 0 \ \text{if} \ i \ \text{and} \ j \ \text{donot share the same border} \end{cases} \end{gathered} \tag{4}$$

Analysis for spatial autocorrelation

The analysis for spatial autocorrelation can judge the existence of spatial autocorrelation of a variable and the degree of spatial correlation. We can make the following judgments through the spatial autocorrelation analysis: if the variable becomes more similar with the shortening of the distance, positive spatial autocorrelation can be identified; if the variable becomes more different with the shortening of the distance, negative spatial autocorrelation can be confirmed; and if the variable does not show any relevance to the shortening of the distance, there is a spatial randomness.

The analysis for spatial autocorrelation is composed of two types: global spatial autocorrelation and local spatial autocorrelation. The global analysis is about the spatial distribution features of an attribute value of a spatial unit in the whole region, while the latter focuses on the spatial correlation between each spatial unit and its contiguous spatial units in a certain attribute value. The global Moran's *I* can be used for judging the global spatial autocorrelation (Moran 1950), and is chosen as the research tool for spatial autocorrelation in this study. Its formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \tag{5}$$

In Eq. (5), n represents the total quantity of space units; x_i, x_j represent the observation values of variables in space units i and j, and w_{ij} represent the contiguous relationship between space units i and j. When i and j are contiguous space units, $w_{ij} = 1$; vice versa, $w_{ij}= 0$. The value for the global Moran's I index lies in the interval $[-1, 1]$.

In order to recognize the local spatial autocorrelation, the value for the local spatial autocorrelation statistics in each space location should be calculated. The formula for the local Moran's I index is as follows:

$$I_i = \frac{(x_i - \bar{x})}{S^2}\sum_{j} w_{ij}(x_j - \bar{x}) \tag{6}$$

Spatial regression analysis

The spatial econometric models previously focused on the spatial autoregressive model with only the spatial lag term of the explained variable and the spatial error model including only the spatial error term. However, the explained variable may also have significant spatial effect (reflected in its spatial lag term) and autocorrelation in the error resulted from random shocks (Anselin et al. 2008). According to this, LeSage and Pace (2009) constructed a spatial Durbin model (SDM), which comprehensively reflects the above two spatial effect mechanisms. Considering the spatial spillover of RETI, the direct effect of a series of explanatory variables on innovation in a province and their indirect effect on innovation in other contiguous provinces, this study adopts SDM to make its analysis.

The simplified form of the SDM is shown in Eq. (7), where W represents a spatial weight matrix of $N \times N$, y denotes a vector of the observation values for the explained variable, Wy represents a vector of the observation values for the spatial lag term of the explained variable, ρ represents the coefficient for measuring the spatial lag effect of the explained variable (i.e., the endogenous coefficient for the spatial interaction term), x denotes a vector set of the observation values for the explanatory variables, α denotes a constant parameter, β represents a vector of the coefficients for the explanatory variables, Wx represents a vector set of the observation values of the spatial lag term of the explanatory variables, γ denotes a vector of the coefficients for the spatial lag term of the explanatory variables, and ε denotes the model residual.

$$y = \alpha + \beta x + \rho Wy + \gamma Wx + \varepsilon \tag{7}$$

On the basis of the variable selection, data collection, and model specification, this study will conduct a spatial statistical and econometric analysis on the model.

Results

Spatial variation assessment

Figure 3 illustrates the patent counts, based on the application date, for renewable energy across the 29 provinces of China up to December 2017. As shown in Fig. 3, these patent counts show a high degree of spatial heterogeneity in the 29 provinces. Some provinces have a high level of RETI, while other provinces have a low level of RETI.

Spatial autocorrelation analysis

Although Fig. 3 shows that in 2017, the patent counts for renewable energy in the 29 provinces showed a high degree of spatial heterogeneity, it is still difficult to determine whether this spatial heterogeneity is random or there is a certain spatial organization. In order to study whether there is spatial association between these patent counts in local provinces and those in the surrounding provinces, this study uses the global Moran's I test for conducting the analysis of global spatial autocorrelation. The global Moran's I of the renewable energy patent applications in the 29 provinces is 0.409 (p value < 0.001), which shows that RETI significantly deviates from the random distribution. This reflects the significant positive spatial association between RETI in specific provinces and their adjacent provinces and shows that the closer the distance between provinces is, the more obvious the spatial association of RETI is, that is, RETI in the neighboring provinces shows the trend of clustering. However, the global Moran's I only describes the total concentration of RETI in the 29 provinces and cannot clarify the specific concentration characteristics of a province. Therefore, the local Moran's I should be employed for analyzing the local spatial correlation and variation of each province in order to make up for the possible defects of the global spatial autocorrelation. The results for the local indicators of spatial correlation analysis for this study are shown in Fig. 4. The provinces highlighted in dark blue represent the clusters of provinces with low levels of RETI, which indicates that these provinces are cold spots of RETI. These cold clusters seem to cover Hunan, Guizhou, Yunnan, Ningxia, Qinghai,

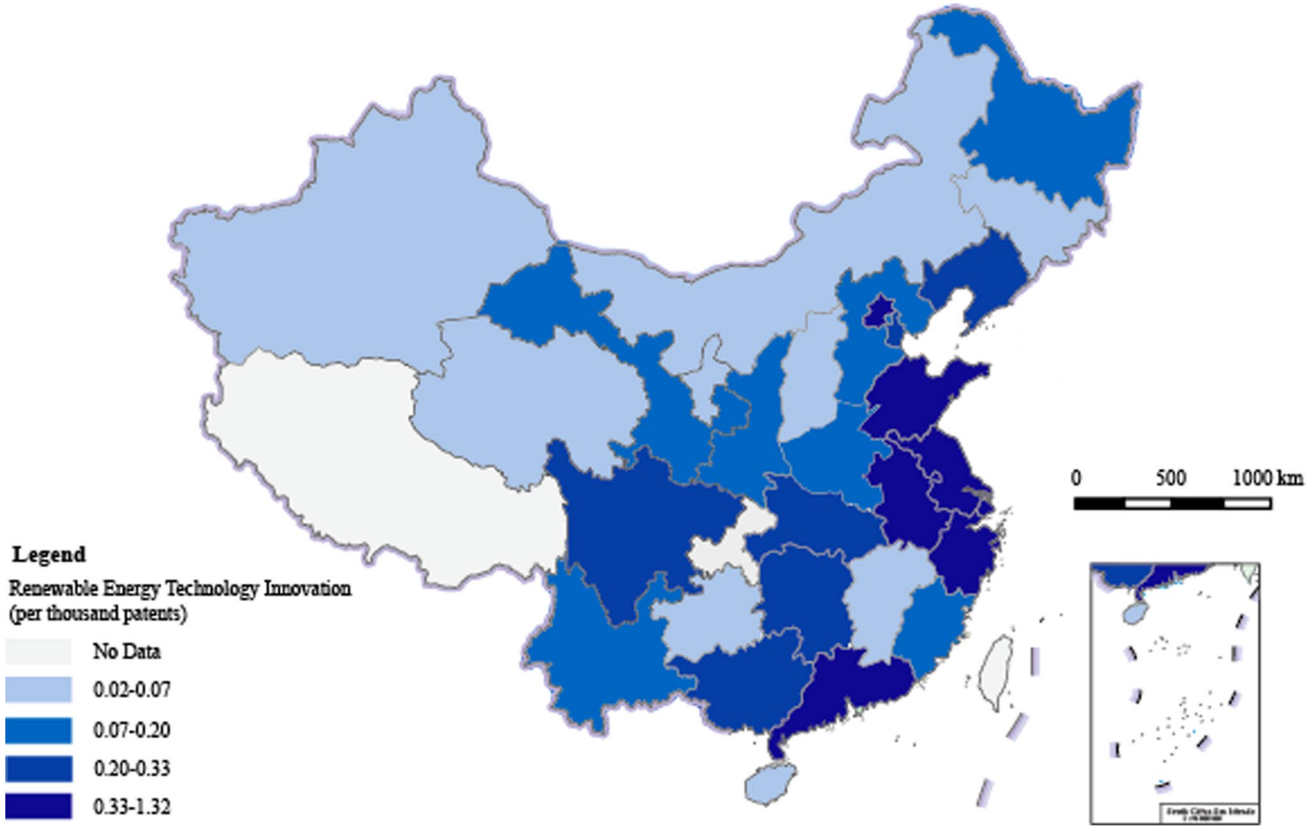

Fig. 3 Choropleth map of renewable energy technology innovation per 1000 patents across the 29 provinces of China up to December 2017

Xinjiang, Gansu, Inner Mongolia, Shaanxi, Shanxi, and other provinces. Comparatively speaking, Beijing, Jiangsu, Zhejiang, Shandong, and other provinces have been identified as hot spots of RETI (highlighted in dark red).

Correlation analysis

This study makes a series of correlation analyses to explore whether RETI in the local provinces is related to other characteristics of these provinces. The Spearman's rank method was used for the correlation analysis. A series of regional characteristics are considered, including the—R&D intensity of the enterprises, research institutions, and universities, the human capital, the marketization indicator, and the installed capacity in the local provinces (see Table 4 for details).

The results show that RETI has significant correlation with most of the regional characteristic variables. It is worth noting that a positively strong correlation is confirmed between university R&D intensity and research institution R&D intensity (rs: 0.877), between R&D intensity of enterprises and marketization indicator (rs: 0.707), between RETI and the human capital (rs: 0.686) and marketization indicator (rs: 0.639), and between the human capital and marketization indicator (rs: 0.634). In addition, the results revealed the existence of a positively moderate correlation between RETI and enterprise R&D intensity (rs: 0.501) and enterprise R&D intensity and human capital (rs: 0.502). In contrast, only a weak positive correlation is identified between RETI and the university R&D intensity (rs: 0.314) and research institution R&D intensity (rs: 0.303). In addition, only a weak positive correlation is confirmed between enterprise R&D intensity and university R&D intensity (rs: 0.285), research institution R&D intensity and marketization indicator (rs: 0.243), and the R&D intensity of the universities and marketization indicator (rs: 0.385).

Regression analysis

In order to explore the relative importance of a series of driving factors for RETI, a series of regression models are set up and analyzed. Firstly, the data in this study pass the unit root test (Pesaran 2007), which indicates that the data are stationary. Secondly, an OLS model with clustered robust standard errors is used for estimation in this study (Hoechle 2007; Zhen et al. 2015; Ren et al. 2017), which better solves the autocorrelation problem in the panel data. Lastly, to eliminate the influence of variable dimensions and heteroscedasticity to a certain extent, this study

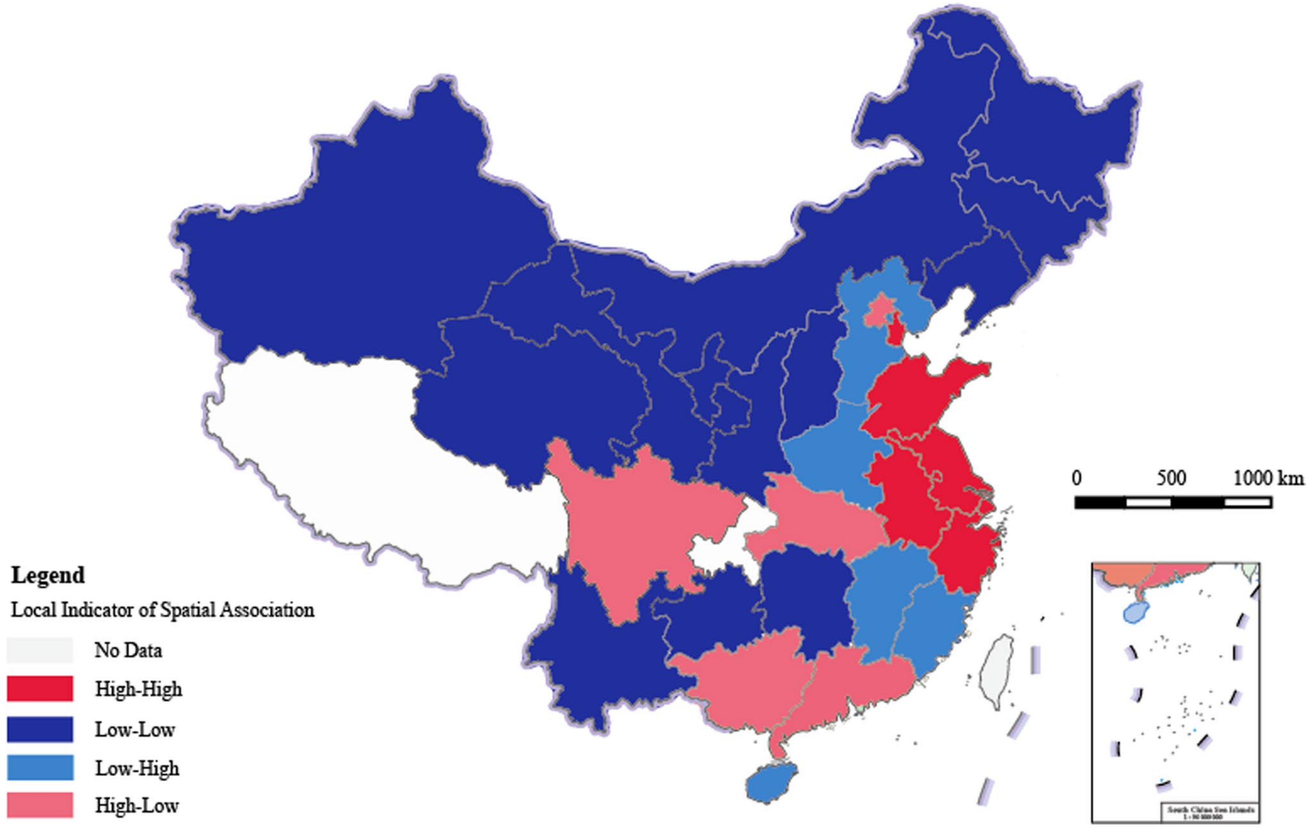

Fig. 4 Local spatial autocorrelation analysis of renewable energy technology innovation per 1000 patents across the 29 provinces of China

Table 4 Correlation analysis

	reti	erdi	srdi	urdi	hc	mi	reic
reti	1						
erdi	0.501***	1					
srdi	0.303***	0.0750	1				
urdi	0.314***	0.285***	0.877***	1			
hc	0.686***	0.502***	− 0.0330	− 0.0430	1		
mi	0.639***	0.707***	0.243***	0.385***	0.634***	1	
reic	0.0710	− 0.134**	− 0.171***	− 0.235***	0.0730	− 0.130**	1

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively

standardizes the explained variable and a series of explanatory variables and transforms them into their natural logarithm.

Through the correlation analysis in "Correlation analysis" section, we find that there are a series of strong positive correlations between different explanatory variables, such as the university R&D intensity and research institution R&D intensity (rs: 0.877), enterprise R&D intensity and marketization indicator (rs: 0.707), RETI and human capital (rs: 0.686), RETI and marketization indicator (rs: 0.639), and human capital and marketization indicator (rs: 0.634). To a certain extent, this naturally raises the question of multicollinearity. Multicollinearity refers to the inaccuracy of regression estimation due to the high correlation between the variables in multivariable linear regression. Therefore, it is necessary to conduct a multicollinearity test to ensure that this situation will not have a negative impact on the estimation effectiveness of the regression model in this study. Accordingly, the variance inflation factor (VIF) was employed to test the multicollinearity according to the criteria proposed byFreund et al. (2006).[6] In this study, the VIF of all the variables in each model is below 10, so the

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[6] According to Freund et al. (2006), it is considered to be acceptable when $0 < VIF < 10$; it means there is multicollinearity when $10 \leq VIF < 100$; and it means there is strong multicollinearity when $VIF \geq 100$.

Table 5 Benchmark ordinary least squares and SDM regression models

	OLS (model 1)		SDM (model 2)					
			Total		Direct		Indirect	
	Beta	*t* value	Mean	*z* value	Mean	*z* value	Mean	*z* value
intercept	−2.1611***	−3.25						
lnerdi	0.1090***	5.14	0.2904***	5.38	0.0934***	4.68	0.1970***	4.21
lnsrdi	0.0677***	3.03	0.2000***	3.36	0.0511***	2.63	0.1489***	2.82
lnurdi	−0.0087	−0.45	0.0128	0.24	−0.0054	−0.31	0.0182	0.40
lnhc	0.2544***	3.38	0.3226	1.58	0.1952***	2.81	0.1274	0.66
lnmi	0.0964*	1.82	−0.0609	−0.57	0.0266	0.57	−0.0875	−0.94
lnreic	0.0002	0.04	0.0056	0.47	0.0046	0.86	0.0010	0.10
rho			0.1846***	2.94				
Observations	348		348					
R-squared	0.598		0.391					
Model diagnostics								
Robust LM (spatial lag)	32.94***							
Robust LM (spatial error)	19.49***							
LR test (spatial fixed effects)			363.29***					
LR test (time-period fixed effects)			36.66***					

***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively

multicollinearity problem in our estimation is within the acceptable range.

In order to identify whether there is a model misspecification caused by the omission of the spatial lag term of the explained variable or the spatial autocorrelation term of the error term in the model, this section carries out the robust LM (Lagrange multiplier) test. The results for the benchmark ordinary least squares (OLS) model (model 1) indicate that the test values of the robust LM (spatial lag) and robust LM (spatial error) both have a significance level of 1%, which reveals that bringing the spatial lag term of the explained variable and the spatial autocorrelation term of the error term in the model into the benchmark model can improve the goodness of fit of the model.[7] Therefore, according to the test results of the robust LM, combined with the recommendations of LeSage and Pace (2009), this study will establish an SDM. Furthermore, the LR (likelihood ratio) test is employed to judge the applicability of a fixed effects model or random effects model. In accordance with the LR test results, test values of the LR test (spatial fixed effects) and LR test (time-period fixed effects) have a significance level of 1%, which indicates that a two-regime SDM with spatial and time-period fixed effects (model 2) can be applicable. The regression results of the benchmark OLS model (model 1) and two-regime SDM including spatial and time-period fixed effects (model 2) are shown in Table 5.

As indicated from Table 5, the R&D intensity of the enterprises and research institutions, as well as human capital, have significantly positive direct effects on RETI (at a level of 1%). In terms of the relative importance of the direct effects, local human capital is the most important factor driving RETI (β: 0.1952) followed by enterprise R&D intensity (β: 0.0934) and research institution R&D intensity (β: 0.0511), which indicates that RETI is higher in areas with high levels of local human capital, high levels of R&D intensity of local enterprises, as well as high levels of R&D intensity of local research institutions. However, the direct effect coefficient of the university R&D intensity is negative (β: − 0.0054) but not significant. In addition, in the estimation of the SDM, it is also confirmed that there are two positive, but not significant, direct effects: the local institutional quality (β: 0.0266) and industrial scale (β: 0.0046). This shows that the current institutional quality and industrial scale of each province in China do not have significant impacts on promoting RETI, while the R&D intensity of the local universities (β: − 0.0054) does not have a significant impact on enhancing the local RETI but may also play a certain role in inhibiting it, although this role is not significant. In contrast, only the R&D intensity of the enterprises and research institutions have significant positively indirect effects on RETI (the significance level is $p < 0.01$), while the indirect effects of the other factors (including the university R&D intensity, human capital, marketization indicator,

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[7] LeSage and Pace (2009) suggested that we consider the spatial Durbin model in this situation.

and renewable energy installed capacity) on RETI are not significant.

Discussion

1) In terms of the direct effect, the local human capital is the most important factor driving RETI (β: 0.1952, $p < 0.01$), but the indirect effect coefficient of human capital is not significant (β: 0.1274, $p > 0.1$), which indicates the insignificant spatial spillover effect of human capital on RETI in surrounding provinces.

   To some extent, this is because the management system of China's human capital market is not yet fully developed (Li et al. 2021; Wang et al. 2021). A unified and open human capital market in China has not yet formed, which influences the fundamental effect of the market mechanism on the distribution of the human capital. Additionally, the flow of the human capital has been still restricted by the ownership system, housing system, and social security system, and the institutional barriers have not been eliminated, which have resulted in a clear segmentation of the human capital investment among various provinces (Liu and Lei 2017). Moreover, some studies show that, on the basis of the resource curse hypothesis, the development prosperity of the resource rich regions in China not only affects the flow of the production factors, including the human capital, among different departments, but it results in the development of deindustrialization. This also seriously affects the cross regional flow of the production factors, including the human capital, which results in the great difference in the distribution of the human capital among different regions in China (Xie 2012). Generally speaking, the reasonable flow and optimal allocation of talents between different provinces in China are still hindered, which can affect the indirect spatial spillover of the local human capital on the technological innovation in the surrounding areas. Furthermore, the opportunity of economic practice in an economic society determines the scale, speed, and characteristics of the formation of human capital, and the degree of economic practice depends on the economic freedom given to people by the economic system, which is the mechanism by which the transformation of China's economic system affects the accumulation and formation of human capital (Zhang 2007). Therefore, the degree of economic freedom given by the institutional transformation in different regions will greatly affect the spatial spillover effect of the human capital on innovation in surrounding areas. To summarize, this study holds that the imperfect human capital market management system and market operation mechanism among different regions in China are the main factors restricting the spatial spillover effect of human capital.

2) In terms of the relative efficacy of the R&D intensity from different sources, the direct effect (the coefficient is 0.0934, and the significance level is 1%) and indirect effect (the coefficient is 0.1970, and the significance level is 1%) of the R&D intensity of the enterprises are the strongest. The direct effect (the coefficient is 0.0511, and the significance level is 1%) and indirect effect (the coefficient is 0.1489, and the significance level is 1%) of the R&D intensity of the research institutions are the second strongest, while the direct effect (the coefficient is – 0.0054, and the significance level is 10%) and indirect effect (the coefficient is 0.0182, and the significance level is 10%) of the R&D intensity of the universities are not significant.

   This shows that for all the provinces and cities in China, the enterprises R&D intensity as well as research institutions R&D intensity are the main sources of funds for RETI in the local and surrounding provinces. In contrast, the universities R&D intensity is not the main source of funds for RETI in the local and surrounding provinces.

   According to the results of this study, universities R&D intensity is not the main source of funds for RETI in local and surrounding provinces. This is partly the following reasons. First, the innovation abilities of the universities in different provinces present obvious differences. The innovation abilities of the universities in the eastern provinces are the highest, the central provinces are in the middle, and the western provinces are the lowest (Yang and Han 2013). As most of the universities with strong innovation ability in China are concentrated in Beijing, Shanghai, Jiangsu, and other developed provinces and cities, IURC is also more concentrated in these provinces and cities. As far as the whole of China is concerned, IURC shows a significant spatial imbalance. Specifically, in the regions with strong innovation ability, the universities show a significant spatial spillover effect in interactive communication with the surrounding regions, whereas in the regions with weak innovation ability, the universities only have insignificant spatial spillover effects (Wu 2016). Therefore, the uneven spatial distribution of the universities with strong innovation ability in China may lead to the insignificant or even negative effect of the university R&D intensity on RETI. Second, foreign-funded enterprises investing in renewable energy will face national cultural differences when they conduct R&D cooperation with Chinese universities. When many foreign enterprises cooperate with Chinese universities, a lot of problems are caused by cultural differences. The conflicts and misunderstandings brought by these cultural differences will create obstacles to knowledge spillover and the decline of the work efficiency (Ming-Hsin and Hung-Hsin 2008). Specifically, the cultural differences between China and other countries are bound to bring severe challenges to China's renewable energy investment (Huang, 2014), which in turn may form different R&D environments and cause a decrease in innovation efficiency. Considering the differences between the Chinese and western cultures, the magnitude of R&D cooperation between the enterprises and universities in China is often not as close as it is in western countries; Chinese universities care more about the scale of projects, and the cooperation contract is not so clear and transparent. Therefore, there is less communication in IURC in China, so it is urgent to strengthen the establishment of a more formal project mechanism.

The R&D investments of enterprises and research institutions are the main sources of financing for RETI in the local and surrounding provinces. Active investment in R&D is an effective strategy for enterprises to absorb and integrate external technical resources (Guo 2008). Renewable energy is a capital-intensive industry, so its technology innovation needs a lot of early investment (Xu and Lin 2018). Enterprises represent the main body of a country's technological innovation, so their R&D investment dominates in a country's innovation process. Because of the increasingly fierce competition among enterprises, in order to obtain higher profits, enterprises should take market demand as their guide and aim to acquire new applied technology and new products while introducing foreign technology, that is, they should raise inputs in their independent R&D and improve the level of independent R&D technology. Thus, enterprises should emphasize making full use of their invested funds. The R&D investment of enterprises may have stronger effects on industrial innovation than government R&D investment (Yan and Gong 2013). In addition, enterprise investment can bring breakthroughs to the R&D resources structure, that is, enterprises can achieve knowledge spillover by taking advantage of market signal feedback and bring new technology and knowledge to themselves through "learning-by-doing." The forms of this include personnel interchanges and demonstration activities, which help firms to make more effective allocations of their innovation resources and effectively lead to the enhancement of industrial innovation (Fan et al. 2011).

The western academic circles represented by Arrow (1962) generally believe that the fundamental reason for the existence of R&D in research institutes lies in the market failure of enterprise R&D activities. Research institute R&D has the characteristics of achievement spillover and non-exclusive innovation benefits, which can provide public technology for the society and solve the problem of market failure. Moreover, research institute R&D expands the technology spillover to enterprises through the transfer and flow process of knowledge, technology resources, and talents so as to reduce the R&D cost and risk of the enterprises. Public research institutions can also reduce the risks and uncertainties inherent in research, solve problems in existing industries and research and development of new technologies, help small and medium enterprises and new industries to develop, and bring them closer to non-corporate actors such as universities (Intarakumnerd and Goto, 2018). Therefore, research institute R&D is complementary to enterprise R&D (Falk 2006).

3) The marketization indicator and installed capacity have no significant effect on promoting RETI. From the perspective of the direct effect, the promotion effect of the marketization indicator ($\beta = 0.0266$) and installed capacity ($\beta = 0.0046$) on RETI are not significant. From the perspective of the indirect effect, the indirect effect coefficient of the marketization indicator is negative and insignificant ($\beta = -0.0875$), and the indirect effect coefficient of the installed capacity is also insignificant ($\beta = 0.0010$). This reveals that the two factors do not have obvious spatial spillover effects on RETI in the surrounding provinces.

The degree of marketization is an important indicator of the transition from the current economic construction to the socialist market economy, which reflects the important role of the market in the overall operation of the socialist economy and in resource allocation. There are obvious differences among the regions in their economic levels, and the degree of marketization varies greatly in different regions. Even in the same region and in different sectors, the degree of marketization plays a different moderating role in enterprise innovation. When the government intervenes in the economy, the influence of marketization on enterprise innovation is more significant (Fan et al. 2003). Therefore, the degree of marketization mainly plays a role by moderating between the subsidies provided by the government and enterprise innovation, which has also been confirmed by Lv (2016). Through the evidence provided by the strategic emerging industry listed companies in 2009–2013, this study shows that the degree of marketization, market competition, and other factors obviously moderate between the subsidies from the government and enterprise innovation. Due to data limitations, we are not able to consider how government subsidies influence RETI in each province, and considering the impact of marketization on RETI alone may lead to insignificant coefficients. Xiao and Lin (2014) argue that the ownership structure of firms indirectly reflects the degree of government intervention in the market. In terms of the ownership structure, due to the high capital entry barriers and technical barriers in the wind turbine manufacturing industry, the domestic wind turbine manufacturing industry is dominated by large-scale state-owned enterprises and has a high monopoly concentration and technology concentration, which to a certain extent weakens the role of marketization indicators. The various obstacles to wind power integration into the grid also cause domestic wind power generation enterprises to be dominated by large state-owned enterprises (Shi and Li 2013). For different ownership enterprises, there will be some differences in the effect of marketization, and the effect of marketization on the innovation of state-owned enterprises is relatively low (Liu 2019). Zhou and Zhang (2014) argue that the effect of marketization is also influenced by the level of regional economic development and openness to the outside world, and the effect of marketization is gradually weakened when the level of economic development and openness is low. The direct effect of marketization indicators is positive, which indicates that marketization indicators can promote local RETI. This result can be explained as follows, the enhancement of marketization level can lead to government intervention reduced, the market competition environment is being improved, the competition in product and factor markets is being intensified, and the legal system is being improved, which stimulates the intrinsic motivation of enterprise innovation activities and thus promotes local RETI (Feng et al. 2011). The negative spatial spillover effect of marketization on neighboring provinces may be due to the fact that marketization reforms have created competitiveness between regions, which has a "crowding out effect" on RETI in neighboring provinces, thus producing a negative spatial spillover effect (Zhang et al. 2019). This explains why the marketization indicator does not have a significant direct effect and, to some extent, a spatial spillover effect from the perspective of the ownership structure.

In recent years some scholars have found that the level and quality of innovation are positively affected by the industrial scale (Nicholas 2015). Some scholars employed the renewable energy installed capacity to measure the industrial scale based on the following considerations. The high installed capacity in a specific region indicates the potential of the renewable energy industry in the region to make full use of the scale effect and achieve its innovation goals in a broader market (Wang et al. 2015). There is no doubt that in the past decade, rapid development has been made in China's renewable energy installed capacity. For example, the installed capacity increased from almost zero at the beginning of the twenty-first century to 221 GW in 2018, which makes it the highest ranked in the world. However, in terms of innovation and competitiveness, China lags behind the developed countries in terms of wind power. Chinese wind turbine manufacturers have only been able to register a few international patents, and the innovation level of the domestic patents is not high; most of them are utility models (Lam et al. 2017). After 2010, some wind power enterprises have emphasized scale development and paid less attention to technological innovation, which has resulted in the gradual exposure of some deep-seated problems in China's wind power industry development, such as resource misallocation (Yu et al. 2021), the challenge of wind power integration and consumption (Dai et al. 2018), and the lack of experience and knowledge accumulation during the rapid expansion phase (Hayashi et al. 2018). As a result, serious overcapacity has taken place in China's wind power industry development, and this has led to a substantial degree of wind power abandonment. According to statistics, China's wind power abandonment was very serious in 2012, when the abandoned wind power amounted to 20.8 billion KWh, with a rate of about 17%. And the abandoned wind rate in the first half of 2015 was even as high as 15.2%. However, the 2018 data shows that the national wind power abandonment rate has dropped from 17% in 2016 to 7.2% in 2018, with the utilization rate of wind power reaching 92.8%.[8] This shows that the overcapacity of wind power in China has now been effectively alleviated, but the overall innovation capacity of renewable energy is still lagging behind compared with the developed countries, and the industrial scale benefit of the renewable energy industry has not been exploited. To some extent, this explains the insignificant direct effect and spatial spillover effect of the industrial scale on RETI.

Conclusions and policy recommendations

The industry development of renewable energy has significant driving effects on China's energy security, low carbon transformation of its energy system, and its climate change mitigation efforts (Wang et. al. 2018). Technological innovation is a critical driving force for renewable energy development. Therefore, it is of great and far-reaching significance for China's energy transformation to deeply explore the drivers affecting innovation for renewable energy technologies.

Using the panel data from China's 29 provinces during 2006–2017, we employed spatial methods to explore the impact of the R&D intensity of enterprises, research institutions and universities, human capital, institutional quality, and industrial scale on RETI. We found that RETI in each province presents obvious spatial heterogeneity and spatial

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[8] http://news.bjx.com.cn/html/20180607/904085.shtml.

association. In fact, in recent years, some studies have paid attention to the cross-regional spatial effect of industrial or regional technological innovation. They found that industrial or regional technological innovation not only shows obvious spatial heterogeneity, but it also generally has significant spatial association, which may exert a very critical impact on the direction and intensity of various factors affecting industrial or regional technological innovation (Wu 2006; Läpple et al. 2016). We conclude as follows. (1) Human capital in the local region is the most important factor driving RETI, but the spatial spillover effect of the human capital in surrounding provinces on the local RETI is not obvious. (2) The R&D investments of enterprises and research institutions are the main sources of funds for RETI in the local and surrounding provinces. In contrast, the R&D investment of universities is not the main source of funds for RETI in the local and surrounding provinces. (3) The institutional quality and industrial scale have no significant effect on promoting RETI in the local province, and their spatial spillover effect on RETI in the surrounding provinces is not obvious.

To investigate the spatial pattern for RETI in China, we expanded the knowledge production function by introducing the human capital, institutional quality, and industrial scale on the basis of the original R&D intensity in the equation (including the three sources of enterprises, universities, and research institutions), and further examined the relative importance of the above factors driving RETI. In terms of the experience from other countries, scholars proved that some similar factors, such as R&D support (Miremadi et al. 2019), regulatory quality (Afrifa et al. 2020), and human capital (Khan et al., 2020), have a very important impact on green technology innovation. It is helpful to identify the key factors restricting RETI in the local and surrounding provinces as they provide important references for governments to help them formulate relevant policies to promote RETI effectively. We put forward the following policy recommendations from the above analysis.

1) At present there are a series of problems in China's human resource market, such as fragmentation, irregular operation, and low efficiency of talent allocation, which are important obstacles to restraining the spatial spillover effect of human capital on technological innovation in the neighboring provinces (Jiang 2011). In order to improve the market-oriented allocation efficiency of the human resources, better play the driving role, and optimize the spatial spillover effect of human capital on RETI, effective policies should be issued by the government to reduce the institutional obstacles of the talent flows so as to promote the establishment of a unified and standardized human resources market nationwide. It is worth mentioning that the promotion of mega urban agglomerations of integrated cities by the government will effectively strengthen the spatial spillover effect of human capital (Zheng and Du 2020), which will thereby help to drive RETI in the urban agglomerations.
2) The government should establish an effective mechanism of IURC to promote the knowledge spillover of universities. In those innovation networks created by IURC, company technicians, university researchers, and entrepreneurs can exchange heterogeneous knowledge through informal exchanges or formal academic seminars, so they can realize the spillover of technical knowledge. As an important source of knowledge spillover, universities provide a platform for the interaction among enterprises, individuals, and government agencies through the forms of technology transfer and through the local employment of students in order to facilitate knowledge spillover (Fischer and Varga 2003). Furthermore, universities play a leading role in the triple helix structure formed by the interaction of the university-industry-government, which can accelerate the process of knowledge flow and promote the innovation of regions (Etzkowitz 2012). Therefore, the government should take a series of policy measures to improve and optimize the construction of IURC organizations, such as the promotion of the university innovation capabilities, the establishment of enterprise technology innovation platforms, and the improvement of the public technology service system (Liu and Huang 2018).
3) The increase of enterprise R&D investment in renewable energy is essentially a feedback on favorable investment conditions, such as the increase in the prices of resources (including oil, natural gas, coal as well as electricity) and the increase in government public support (Arias and van Beers 2013). Thus, the government should emphasize increasing public financial support for enterprise R&D and the timely increase in the prices of electricity and other resources (Lin and Chen 2019). Specifically, policies and measures, such as increasing government subsidies and tax incentives and project investment in R&D, can be adopted to encourage enterprises' R&D investments (Lin and Zhu 2019).
4) According to the research of Dai and Liu (2013), industrial characteristics significantly moderate between the marketization degree and industrial innovation. Generally speaking, in industries with low monopoly characteristics and low technology concentration, the impact of marketization on industrial innovation will be more significant. Considering that most of China's renewable energy enterprises are large-scale state-owned enterprises with high degrees of monopoly concentration and high degrees of technology concentration, this situation can better explain why the marketization indicator in this study, as an agent variable of the institutional quality, has no significant effects on driving RETI of the local province and no obvious spatial spillover impacts on RETI in surrounding provinces. In

terms of enhancing the driving effect of the institutional quality on industrial innovation, first, the government should strive to create a fair market environment so the market can fully realize its role in the allocation of the innovation elements, that is, the government should further liberalize market access, reduce administrative monopolies, and strengthen property rights protection. Second, too much government intervention in the renewable energy development has caused the imbalanced dynamic mechanism for industrial development, and also brought about the insignificant driving effect of the industrial scale on industrial innovation (He et al. 2016). Therefore, it is urgent to reduce unnecessary government intervention and improve the performance evaluation system of local governments to enhance the healthy and sustainable development for the renewable energy industry. In addition, the legal environment also needs to be in place to enhance the marketization in China. Therefore, the government should take effective measures to create a good legal environment and strengthen the protection of intellectual property rights in order to create a safe and reliable "soft environment" for industrial innovation.

Author contribution Zheng-Xia He: conceptualization, data curation, writing—original draft preparation. Leyi Kuai: visualization, investigation. Xin Chen: methodology, software, supervision. Wen-Xing Shen: software, validation. Wenbo Li: Writing—reviewing and editing.

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Data availability The datasets used or analyzed during this study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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