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Spatiotemporal patterns and determinants of renewable energy innovation: Evidence from a province-level analysis in China

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China's renewable energy innovation is essential for realizing its carbon neutrality targets and the low-carbon transition, but few studies have spatially examined its characteristics and spillover effects. To fill the research gap, this study investigates its distribution and trends from a spatiotemporal dimension and focuses on the spatial effects of the influencing factors to identify those that have a significant impact on renewable energy innovation by using China's provincial panel data from 2006 to 2019. The results show the following findings. (1) Renewable energy innovation shows distinct spatial differences across China's provinces such that it is high in the east and south and low in the west and north, which exhibits spatial locking and path-dependence. (2) There is a positive spatial correlation with renewable energy innovation. (3) R&D investment and GDP per capita significantly promote renewable energy innovation, but the former effect is mainly observed in the local area, whereas the latter shows spatial effects. More market-oriented policies should be taken for the improvement of renewable energy innovation and the establishment of regional coordination mechanisms are proposed.

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Introduction

As an effective tool to reduce greenhouse gas (GHG) emissions and combat climate change, renewable energy has witnessed rapid development over the past two decades (IEA, 2022a). China had become the world's largest producer of wind and solar energy as of 2017, as well as the largest domestic and outbound investor in renewable energy (Chiu, 2017). By 2021, China accounted for 46% of global renewable energy growth and renewable energy generation accounted for 29.9% of its electricity consumption according to recent statistics reported by the International Energy Agency (IEA, 2022b). When we observe the spatial pattern changes of economic growth and carbon emissions from a global perspective for the period 1960–2016, it was found that the centers of gravity of GDP and CO_2 emissions are shifting towards the east (Balsa-Barreiro et al., 2019). This shift was especially prominent in the case of CO_2 emissions, highlighting that the economic growth model of some countries located in the world's east demanded high levels of resource consumption. This was also particularly evident in China. However, China now demonstrates signs of economic maturity, exhibiting greater efficiency in the consumption of resources and energy. The story that lies behind these figures is the positive association between technological innovation and renewable energy generation capacity (Geng and Ji, 2016; Lin and Zhu, 2019a; Zheng et al., 2021). For example, China became the world's manufacturing powerhouse in several key energy technology sectors, including solar photovoltaics (PVs), wind turbines, and batteries for electric vehicles (EVs) (IEA, 2022a). China's leadership in renewable energy innovation may ultimately lower its production costs and establish its commercial presence globally (Liu and Liang, 2013). According to the Consumer News and Business Channel (CNBC, 2022), BYD company —which has become one of the top three automakers due to its high sales volume of EVs—is such a case in point. Going forward, renewable energy innovation will play a crucial role in achieving China's objectives of carbon peaking by 2030 and neutrality by 2060 and ranks among its core priorities for the 14th Five-Year Plan period (2021–2025).

The primary aim of renewable energy innovation is environmental alleviation and climate mitigation. Research has confirmed its beneficial effects in alleviating nitrogen oxide (NO_x) and respirable suspended particle (PM_{10}) concentrations, but it does not affect sulfur dioxide (SO_2) (Zhu et al., 2020). Carbon dioxide (CO_2) emissions have been shown to be stimulative to innovation (Lin and Zhu, 2019b; Wang et al., 2018). Renewable energy innovation in China is stimulated by multiple factors. Except for the commonly recognized influencing factors of government- and enterprise-supported research and development (R&D) investment (Huang et al., 2012; Lin and Zhu, 2019a), CO_2 emissions have also been found to be an essential driving force in innovation processes, thus implying that they actively respond to climatic changes (Lin and Zhu, 2019a). At present, there is no consensus on whether energy prices play an active role in improving technological progress in renewables, as Liu et al. (2020) argue that energy prices stimulate China's renewable energy innovation while Lin and Zhu (2019a) find a non-significant association between them. The underlying reasons for such contradictory results may lie in the different indicators and methods employed in individual studies.

Regardless of the fact that innovation positively affects renewable power generation (Zheng et al., 2021), the positive association between China's renewable energy innovation and green productivity growth is confined to the wealthier regions, and this effect is amplified as income increases (Yan et al., 2020). It is worth noting that China is also the main exporter of renewable technologies, and developed countries with high renewable energy demand are increasingly importing Chinese solar PV components (Groba and Cao, 2015). In addition, renewable energy innovation in provincial China is characterized by heterogeneity in terms of developmental level and growth rate: the provinces with higher levels of industrialization, R&D investment, and environmental regulation are usually associated with greater innovation and higher growth rates (Bai et al., 2020; Zhao et al., 2022).

Based on the preceding discussion, we identify the following gaps in the literature. First, the existing studies fail to investigate the spatiotemporal characteristics of China's renewable energy innovation in depth. Second, the research on the driving forces of renewable energy innovation focus on the direct effects of those factors, which are mostly analyzed using the negative binomial (e.g., Schleich et al., 2017; Li and Shao, 2021) and panel error correction models (e.g., Lin and Chen, 2019; Galeotti et al., 2020; Ren et al., 2021) without considering their spatial effects. However, there is a spatial effect in the influencing factors that are likely to have an important impact on local renewable energy innovation. The importance of spatial effects for innovative research lies in the fact that, first, according to the economic geography literature (e.g., Levin and Reiss, 1989; Syverson, 2011), geographical concentration stimulates firms' innovative activity, which allows new knowledge to create positive externalities through spatial spreading. Therefore, local innovation will inevitably be influenced by neighboring regions. Studies that only focus on the impact of the temporal dimension and assume that two adjacent regions are independent of each other are inconsistent with reality. Third, for China, when examining the performance of local government officials, the central government compares the economic performance of other regions and draws final conclusions by comparing differences between regions, which is highly correlated with the promotion of provincial leaders (Li and Zhou, 2005; Nie and Li, 2013; Deng et al., 2019). As a result, there is imitation and competition between provinces in terms of their economic behavior, which includes innovation—especially in geographically adjacent provinces or provinces with similar levels of economic development. To fill these research gaps, our study focuses on the spatial characteristics of renewable energy innovation at the province level in China and explores their determinants. We use the standard deviational ellipse method to analyze the spatiotemporal characteristics as well as the pattern changes in China's renewable energy innovation in detail. In addition, the spatial Durbin model is adopted to analyze the effects of the drivers of renewable energy innovation, including the direct, indirect, and total effects.

Three novel contributions are made. First, despite the existence of time-series analyses on the impact of renewable energy innovation on power generation, environmental pollution, and climate mitigation, few studies examine its developmental path and determinants from a spatiotemporal dimension. This study seeks to fill this gap using spatial statistical methods and econometric models based on data from China's national patent system obtained by manual search. Second, we have come to a new discovery that contradicts public perception, because the spatial distribution of renewable energy innovation and the distribution of resources in China show opposite characteristics and a gradual southward shift in an opposite direction to the distribution of resources. This helps us understand that the nature of renewable energy innovation is not such that provinces with abundant basic resources have stronger innovation capabilities, and there may be other important spatial influencing factors that affect innovation. Third, previous discussions on the influencing factors of renewable energy innovation have mainly focused on direct effects and overlooked spatial effects. Our study, therefore, focuses on the spatial effects of the influencing factors to identify those that have a significant impact on renewable energy innovation.

The remainder of this paper is organized as follows. Section "Hypothesis and theoretical framework" reviews the relevant studies. Section "Data and methods" introduces the study variables, data sources, and empirical modeling methods. Section "Empirical results" presents the empirical results and Section "Discussion" discusses their significance. Section "Conclusions and policy implications" concludes and presents several targeted policy suggestions.

Hypothesis and theoretical framework

Spatiotemporal pattern of renewable energy innovation. China's renewable energy resources, such as solar and hydro energies, are scarce in the East and abundant in the West, but the spatial distribution of renewable energy innovation follows the opposite pattern. Bai et al. (2020) investigated the spatial distribution of the average annual growth rate of the renewable energy innovation index across China's provinces during 1997–2015 and found that it is generally consistent with the "Hu Huanyong" Line—that is, renewable technology development is better in southeastern China than in northwest region, and the gap between the regions widened during that period. This disparity is also reflected in the variations in the number of renewable energy patent grants in China, which is significantly higher—and growing more rapidly—in Southeast than in Northwest China. For example, the number of patent grants for renewable energy technologies in Jiangsu increased from 263 in 2006 to 9808 in 2019, a more than 37-fold increase; those in Guangdong increased by about 27-fold from 287 to 7640 (CNIPA, 2022). By contrast, Beijing only experienced about an 11-fold increase from 620 to 6689, and Sichuan, the largest economy in western China, only granted 2087 grants in 2019, a figure which is much lower than those in the southeastern provinces.

Based on the above analysis, the first hypothesis of this study is thus proposed.

Hypothesis 1: China's renewable energy innovation is stronger in the eastern and southern regions, and this trend has gradually strengthened over time.

Spatial effect of renewable energy innovation. The development of new knowledge and technologies creates positive externalities, so the spatial agglomeration they form is conducive to the specialization and innovativeness of enterprises. This is called the knowledge spillover effect (Schleich et al., 2017). The spillover effect is likely to come from the imitation effect, meaning that less efficient enterprises try to emulate the behaviors of leading companies in closely related industries (Syverson, 2011). Several studies have found that knowledge spillovers play a crucial role in firms' innovation behavior (e.g., Griffith et al., 2006; Adam and Mensah, 2013). Bernini and Galli (2023) found that the innovative activities of neighboring hotels spread across space and generate both agglomeration and competition effects using georeferenced data of the consolidated accounts of Italian hotels.

In the recent energy literature, spillover effects have begun to be considered as an important influencing factor (e.g., Lan et al., 2021; Zhao and Sun, 2022; Liu et al., 2022; Mulder et al., 2023). Zhao and Sun (2022) hypothesized that new energy vehicle industry policies can reduce carbon emissions in the transportation sector in neighboring or economically similar regions, which is verified using the panel data of 30 provinces in China from 2009 to 2018. Mulder et al. (2023) found that severe energy poverty is much more spatially concentrated than income poverty, which they argued is a symptom of the slow diffusion of energy-saving technologies due to a combination of investment barriers. However, few recent studies have analyzed the spatial effects of renewable energy and its innovation.

Zhang et al. (2019) found that China's renewable energy industry exhibits path dependence and spatial stability and that there is an industrial agglomeration effect in its spatial development. Based on data from 24 countries in the European Union, Noseleit (2018) documented that while there are barriers to the spatial impact of renewable energy innovation in the short term, foreign technologies have a stronger impact after a number of years. Spatial dependence plays a relevant role in exploring the impact of certain factors on renewable energy innovation, and the extent of that impact will be underestimated if spatial decay and the diffusion of technology are not considered (Rohe, 2020; Shields et al., 2021). Therefore, the development of renewable energy technology in a region not only depends on the distribution of local resources, market structure, industrial environment, and other factors but is also affected by the spillover of technological innovation from surrounding regions. For geographically adjacent innovation centers such as enterprises and scientific research institutions, it is easier to organize innovation resources through collaboration. In addition, the dynamic flow of innovative elements within the region also produces spatial correlation effects.

Based on the above analysis, the second hypothesis of this study is proposed.

Hypothesis 2: Renewable energy innovation has a positive spillover effect in China such that surrounding provinces with strong renewable energy innovation capabilities will have a positive secondary effect on those in the local province.

Influencing factors of renewable energy innovation. Supplementary Table S1 presents an overview of the prior studies on the determinants of renewable energy innovation. Public R&D is a major technology-push policy supported by government funding. Numerous studies confirm the importance of R&D policies and argue that they can compensate for underinvestment related to technological uncertainty, market imperfections, or knowledge failure (Pizer and Popp, 2008). Increasing public R&D funding can effectively promote renewable energy innovation (Johnstone et al., 2010; Lin and Chen, 2019; Ren et al., 2021; Zhao et al., 2022), especially in wind and solar energy technologies (Kim and Kim, 2015). In Denmark, Germany, Spain, and Sweden, public R&D support is the essential driving force in renewable energy innovation (Lindman and Söderholm, 2016). However, some studies such as Böhringer et al. (2017) and Grafström and Lindman (2017) also illustrated that investment in R&D activities does not have a significant impact on renewable energy innovation in mature industries, although it does in the early development stages and in large-scale projects. Although public R&D is cost-intensive, it is considered a domestic innovation activity and thus has a timelier and more pronounced initial impact compared to those that originate from abroad (Noseleit, 2018).

Studies on the characteristics of national innovation show that they are closely related to national income levels. Fagerberg and Srholec (2008) analyzed the experiences of 115 countries from 1992 to 2004 and found that national innovation is highly positively correlated with per capita income. In the early stages of renewable energy development, its application and innovation will incur high costs—much higher than those incurred by fossil energy. Countries with higher economic bases more readily form a preliminary or niche market for alternative energy, and both governments and enterprises have the ability and motivation to carry out alternative energy innovation activities (Fouquet, 2010). Economic growth also increases electricity consumption, and higher electricity demand impacts the market size and thus necessitates innovation over time (He et al., 2018). Moreover, province-level data in China indicate that economic growth has a significant spillover effect on neighboring provinces (Liu et al., 2022). This spatial effect will lead to this growth being fed back to local innovation systems and enhancing local innovation capabilities.

Based on the above analysis, the third hypothesis of this study is proposed.

Hypothesis 3a: Increasing government R&D investment effectively promotes renewable energy innovation in China and has a pronounced impact on the local province.

Hypothesis 3b: The higher the level of economic development, the higher the level of renewable energy innovation in China's provinces is, and this impact has significant spatial effects.

Theoretical framework. It has been documented that government support is the most important factor in driving renewable energy innovation (e.g., Johnstone et al., 2010; Pitelis et al., 2020; Zhao et al., 2022). We must now determine which types of governments are more willing to adopt policies that support renewable energy. Combined with Hypothesis 3b, regions with higher levels of economic development exhibit greater government support for renewable energy. Government support for renewable energy can be further reflected in three aspects. First, the research and development of renewable energy technologies should be directly supported, which corresponds to **Hypothesis 3a**. Second, renewable energy development plans, such as 5-, 10-, or even 20-year renewable energy development targets, should be formulated. Third, the requirements for environmental quality should be determined according to the level of economic development. The government is inclined to formulate strict environmental regulations, which force enterprises to increase their use of clean energy and renewable technology research and development, which corresponds to **Hypothesis 3b**. In terms of direct effects, these measures can increase the use of renewable energy, compensate for possible market failures in the early stages of research and development, stimulate enterprise innovation, and ultimately promote renewable energy innovation.

From the perspective of spatial effects, local governments' low-carbon policies have an emulation effect, which further promotes renewable energy innovation cooperation in neighboring regions and makes the cross-regional flow of innovation factors (e.g., R&D personnel, capital) more efficient. Thus, spatial effects further promote renewable energy innovation, which corresponds to **Hypothesis 2**. The reason for the emulation effect of low-carbon policies is that China's central government is paying more attention to environmental quality. An important measure taken by the central government is that the environmental quality of the region is considered in the process of evaluating the promotion of local government officials, which emphasizes the role of political incentives in promoting local environmental quality (Li and Zhou, 2005; Karplus et al., 2021). As a result, local government officials have a strong incentive to imitate low-carbon policies—especially renewable energy policies—in geographically or economically similar provinces to improve environmental quality in the region while positioning themselves for future promotions. The theoretical framework is shown in Fig. 1.

Data and methods

Dependent variable. Patents can reflect the innovative performance of an economy in a manner that is attractive to researchers from an output perspective. Despite their shortcomings, patent counts are still the best available source of data on innovation that is readily available and comparable across countries and China's provinces (Johnstone et al., 2010; Geng and Ji, 2016; Cheng and Yao, 2021). Referring to the technology classification of Cheng and Yao (2021), we define renewable energy innovation (REI) as the number of patent grants for six renewable energy technologies, namely, hydro, wind, solar, biomass, geothermal, and ocean.

Explanatory variables. Below we illustrate the explanatory variables used in this study.

Public R&D funding (RD). Increasing government funding in R&D activities can effectively promote renewable energy innovation. Böhringer et al. (2017) reported that public R&D spending plays a positive role in renewable energy innovation in its early developmental stages and in large-scale projects. This study uses public R&D funding to measure government R&D investment.

GDP per capita (GDP). Economic growth corresponds to a higher willingness and ability to engage in renewable energy innovation (Fouquet, 2010; Li and Lin, 2016). Economic growth increases electricity demand and thus necessitates innovation (He et al., 2018). We use per capita GDP to measure economic growth.

Renewable energy installed capacity (REIC). Renewable energy capacity reflects the potential of the renewable energy market (Huber, 2008). According to the learning-by-doing effect, renewable energy can lead to innovation in the development process (Schleich et al., 2017). We choose installed renewable energy capacity as a possible key determinant of renewable energy innovation.

Renewable energy share (RES). Policy goals in China and other Kyoto Protocol countries are focused on achieving a certain proportion of renewable energy sources in the power generation stack (Papież et al., 2018). It is generally believed that the higher the proportion of renewable energy power generation, the more effective the renewable energy innovation will be (Cheon and Urpelainen, 2012). In this study, we test the effect of the proportion of renewable energy power generation on renewable energy innovation.

CO_2 emissions per capita (CO_2). Large-scale CO_2 emissions promote renewable energy innovation (Lin and Zhu, 2019a). CO_2 emissions per capita, therefore, are used to represent the carbon constraints faced by the government and enterprises.

Industrial pollution control investment intensity (IPCII). Researchers believe that environmental regulation motivates enterprises to engage in green innovation and form new competitive advantages (e.g., Galeotti et al., 2020). Referring to Guo and Yuan (2020), this study uses the proportion of industrial pollution control investment in industrial added value to measure environmental regulation.

Data collection. This study uses a balanced panel of 31 regions in China from 2006 to 2019. The patent classification codes of renewable energy technologies are obtained according to the guidelines outlined in the "IPC Green Inventory" on the website of the World Intellectual Property Organization (WIPO). The patent classification codes of different renewable energy technologies are presented in Supplementary Table S2. Chinese renewable energy patent counts are collected on the Patent Search and Analysis System website of the China National Intellectual Property Administration (CNIPA, 2022). Due to the high difficulty in crawling the website, it is difficult to obtain data in batches, so the renewable energy patent data are finally obtained by manually entering the international patent classification

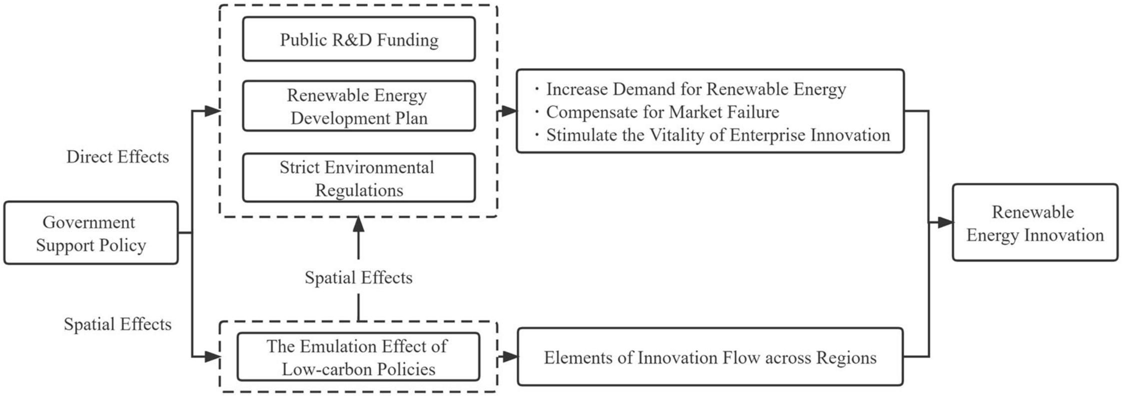

Fig. 1 Theoretical framework. It shows the relationship between government support policy and renewable energy innovation both from the perspectives of direct effects and spatial effects.

Table 1 Variable descriptions.

Variable	Definition and unit	Source
REI	The number of renewable energy patent grants (file)	China National Intellectual Property Administration (2022)
RD	Public R&D funding (RMB 100 million)	China Statistical Yearbook on Science and Technology (2007–2020)
GDP	GDP per capita (RMB)	China Statistical Yearbook (2007–2020)
REIC	Renewable energy installed capacity (million kilowatts)	China Electric Power Yearbook (2007–2020)
RES	The proportion of renewable energy power generation (%)	China Electric Power Yearbook (2007–2020)
CO_2	CO_2 emissions per capita (ton)	China Emission Accounts and Datasets (2022)
IPCII	The proportion of industrial pollution control investment in industrial added value (%)	China Environment Statistical Yearbook (2007–2020)

Missing values were filled using the random forest method.

Table 2 Descriptive statistics.

Variable	Obs.	Mean	Std. dev.	Min.	Max.
REI	434	812.5	1316.0	0.0	9983.0
RD	434	81.6	131.4	0.8	1069.2
GDP	434	44,209.7	27,178.3	6103.0	164,220.0
REIC	434	12.7	14.7	0.0	83.6
RES	434	24.0	26.0	0.0	98.5
CO_2	434	7.3	4.8	0.7	32.9
IPCII	434	0.4	0.4	0.0	3.1

number, the applicant's address, and the publication date for retrieval. There are three types of Chinese patents: invention, utility model, and design.

The IPC classification is only applicable to invention and utility model patents, so we use the number of granted invention and utility model patents as the number of renewable energy patent grants in 31 provinces, municipalities[1], and autonomous regions[2] in mainland China from 2006 to 2019 in our analysis. The RD data are from the China Statistical Yearbook on Science and Technology (2007–2020). The GDP data are from the China Statistical Yearbook (2007–2020). The REIC and RES data are from the China Electric Power Yearbook (2007–2020). The *CO2* data are from the China Emission Accounts and Datasets (CEADs, 2022). The IPCII data are from the China Environment Statistical Yearbook (2007–2020).

This study uses a balanced panel of 31 regions in China from 2006 to 2019. The descriptions, measurements, and data sources of all variables are presented in Table 1. A statistical description of the variables is given in Table 2. All explanatory variables, except renewable energy share and industrial pollution control investment intensity, are logarithmized.

Methods

Standard deviational ellipse. The standard deviational ellipse (SDE) is a classic method for analyzing the directional characteristics of spatial distributions. There are two advantages of using SDE to reveal the spatiotemporal evolution of renewable energy innovation. First, SDE takes the absolute value of geographical elements, which enables quantifying the spatial pattern of different years to the same dimension in comparable studies. Second, this method can accurately capture the relative trend of renewable energy innovation in each province by visualizing that in each year as an ellipse. Accordingly, it is widely used in spatial assessments such as energy consumption (Wang et al., 2022), energy intensity (Shi et al., 2021), carbon emissions (Yang et al., 2020a), and waste management (Richter et al., 2021).

From a global and spatial perspective, this study uses the SDE model to quantitatively explain the overall characteristics of the spatial distribution of renewable energy innovation. The parameters of SDE include the ellipse center, long axis, short axis, and azimuth. The ellipse center represents the center of the research object in the geographical distribution, and the route of motion of the ellipse center in different years represents the spatiotemporal evolution trajectory of renewable energy innovation. The full formula is given in Eq. (1.1); the formulas of the long and short axes are given in Eq. (1.3). The long-axis direction indicates the main directional trend of renewable energy innovation distribution, and the short axis represents its range. The shorter the short axis, the more unbalanced the renewable energy innovation space will be. The azimuth is the angle formed by a clockwise rotation from the north to the long axis, as expressed in Eq. (1.4). The changes in the azimuth denote the differences in the renewable energy innovation growth rates of the four subspaces, which are divided by the long axis and the short axis of the ellipse as follows:

$$\overline{x_i} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \overline{y_i} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{1.1}$$

$$\widetilde{x_i} = x_i - \overline{x_i}, \widetilde{y_i} = y_i - \overline{y_i} \tag{1.2}$$

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n}\left(w_i\widetilde{x_i}\cos\theta - w_i\widetilde{y_i}\sin\theta\right)^2}{\sum_{i=1}^{n} w_i^2}}, \sigma_y = \sqrt{\frac{\sum_{i=1}^{n}\left(w_i\widetilde{x_i}\sin\theta - w_i\widetilde{y_i}\cos\theta\right)^2}{\sum_{i=1}^{n} w_i^2}} \tag{1.3}$$

$$\tan\theta = \frac{\sum_{i=1}^{n} w_i^2\widetilde{x_i}^2 - \sum_{i=1}^{n} w_i^2\widetilde{y_i}^2 + \sqrt{\left(\sum_{i=1}^{n} w_i^2\widetilde{x_i}^2 - \sum_{i=1}^{n} w_i^2\widetilde{y_i}^2\right)^2 + 4\left(\sum_{i=1}^{n} w_i^2\widetilde{x_i}\widetilde{y_i}\right)^2}}{2\sum_{i=1}^{n} w_i^2\widetilde{x_i}\widetilde{y_i}} \tag{1.4}$$

where (x_i, y_i) $(i = 1, 2, \ldots, n)$ represents the longitude and latitude coordinates of region i, w_i represents the REI in region i $(\overline{x_i}, \overline{y_i})$, is the longitude and latitude coordinates of the REI-weighted mean center, σ_x and σ_y are the distances of the long and short axes in the SDE, and θ is the azimuth.

Spatial autocorrelation. With the deepening of China's regional integration, the spatial organization of coordinated development in formations such as urban agglomerations, economic belts, and watershed belts has been continuously enhanced. This in-depth integration will inevitably promote the spatial coordination of regional industries and trigger the flow and diffusion of production factors across regions, thereby building a collaborative environment that enables the spillover of renewable energy innovation. Therefore, it is necessary to thoroughly investigate the spatial distribution pattern and evolutionary trends of China's provincial renewable energy innovation from a spatial correlation perspective. Our exploratory spatial data analysis includes global spatial autocorrelation (GSA) and local spatial autocorrelation (LSA) (Anselin, 2003). GSA is used to describe the spatial distribution characteristics of the entire study area, usually using the global Moran's I test. The global Moran's I can be calculated by Eq. (1.5):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{1.5}$$

where I is the global Moran's I, n is the number of regions studied, w_{ij} is the spatial weight, x_i is REI in region i, and $\bar{x}$ is the mean REI of all regions. I ranges from $[-1, 1]$. If the value is >0, there is a positive spatial autocorrelation of renewable energy innovation among regions. The greater the value, the more obvious the spatial agglomeration phenomenon is.

The Moran scatterplot in the LSA tools can directly reflect the local spatial agglomeration characteristics of renewable energy innovation (Shi et al., 2019). The local Moran's I can be calculated by Eq. (1.6):

$$I_i = \frac{\left(x_i - \bar{x}\right)\sum_{j=1}^{n} w_{\text{ij}}\left(x_j - \bar{x}\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{1.6}$$

Four agglomeration patterns can be obtained using the local Moran's I test, namely, the high–high cluster (H–H; high-efficiency zone), the low–low cluster (L–L; low-efficiency zone), the low–high cluster (L–H; hollow zone), and the high–low cluster (H–L; polarization zone). Specifically, H–H indicates that regions with a high REI are surrounded by other regions with a high *REI*.

The spatial weight matrix $\boldsymbol{W}$ plays a crucial role in determining the model specification. This study considers four spatial weight matrices: the adjacent weight matrix ($\boldsymbol{W}^{0-1}$), geospatial weight matrix ($\boldsymbol{W}^{\text{g}}$), economic-distance weight matrix ($\boldsymbol{W}^{\text{e}}$), and geospatial & economic-distance weight matrix ($\boldsymbol{W}^{\text{ge}}$). The specific setting formulas are as follows:

$$w_{ij}^{0-1} = \begin{cases} 1, \text{if region } i \text{ and } j \text{ are adjacent} \\ 0, \text{otherwise} \end{cases} \tag{1.7}$$

$$w_{ij}^{\text{g}} = \begin{cases} 1/d_{ij}^2, & i \neq j \\ 0, & i = j \end{cases} \tag{1.8}$$

$$w_{ij}^{\text{e}} = \begin{cases} 1/\left|X_i - X_i\right|, & i \neq j \\ 0, & i = j \end{cases} \tag{1.9}$$

$$w_{ij}^{\text{ge}} = \begin{cases} 1/\left(d_{ij}^{2*}\left|X_i - X_j\right|\right), & i \neq j \\ 0, & i = j \end{cases} \tag{1.10}$$

where d_{ij} is the geospatial distance between region i and region j, and X_i represents the average per capita GDP of region i from 2006 to 2019. The spatial weight matrix is row-standardized.

Spatial panel model. According to the theoretical construct of "economic geography," everything is essentially connected in space, and the shorter the distance, the closer the connection is. With respect to the spatial correlation of renewable energy innovation between regions in China (Zhu et al., 2020), this study adopts a spatial panel model to explore the spillover effects and drivers of renewable energy innovation (Belotti et al., 2017). The general form of the spatial Durbin model is shown in Eq. (1.11):

$$\begin{aligned} \ln \text{REI}_{it} = {} & \rho \sum_{j\neq i,j=1}^{n} w_{ij} \ln \text{REI}_{jt} + \beta_1 \ln \text{RD}_{it} + \beta_2 \ln \text{GDP}_{it} + \beta_3 \ln \text{REIC}_{it} \\ & + \beta_4 \text{RES}_{it} + \beta_5 \ln \text{CO}_{2it} + \beta_6 \text{IPCII}_{it} + \gamma_1 \sum_{j\neq i,j=1}^{n} w_{ij} \ln \text{RD}_{jt} \\ & + \gamma_2 \sum_{j\neq i,j=1}^{n} w_{ij} \ln \text{GDP}_{jt} + \gamma_3 \sum_{j\neq i,j=1}^{n} w_{ij} \ln \text{REIC}_{jt} + \gamma_4 \sum_{j\neq i,j=1}^{n} w_{ij} \text{RES}_{jt} \\ & + \gamma_5 \sum_{j\neq i,j=1}^{n} w_{ij} \ln \text{CO}_{2jt} + \gamma_6 \sum_{j\neq i,j=1}^{n} w_{ij} \text{IPCII}_{jt} + \mu_i + v_t + \varepsilon_{it} \end{aligned} \tag{1.11}$$

where ρ represents the spillover effect, which reflects the impact of renewable energy innovation in spatially related areas on that in local areas. w_{ij} is the spatial weight, μ_i indicates individual fixed effects, v_t indicates time fixed effects, and ε_{it} is the random disturbance term that obeys independent and identical distributions and satisfy $\varepsilon_{it} \sim \text{iid}\ (0, \sigma^2)$.

The estimated coefficient is not strict enough to directly reflect the marginal effect of the explanatory variable on the dependent variable and is only valid in the direction of action and at the significance level. Therefore, this study conducts partial differential decomposition following Lesage and Pace (2009) and examines the direct and indirect effects of each explanatory variable. The former measures the impact of a change in a local explanatory variable on renewable energy innovation in the region, while the latter measures the impact of a change in a local explanatory variable on that in adjacent areas—that is, the spillover effect of an explanatory variable.

Empirical results

China's renewable energy innovation profile. This section introduces the current status of China's renewable energy innovation. Figure 2 shows the number of six types of renewable energy patents granted in China from 2000 to 2019. Under the guidance of the national strategy and policy for developing renewable energy, and in particular, the *Renewable Energy Law of*

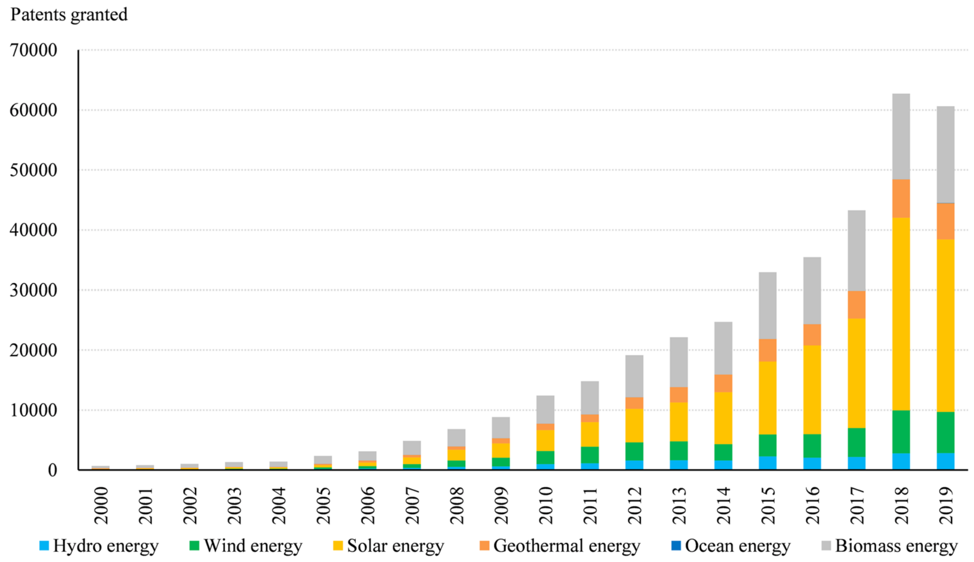

Fig. 2 Granted renewable energy patent numbers in types from 2000 to 2019. A description of REI in China from 2000 to 2019 using data from the China National Intellectual Property Administration.

Fig. 3 Spatial distribution of REI in China in 2006. A spatial distribution description of REI in China in 2006.

the People's Republic of China promulgated in 2005 (NEA, 2017), renewable energy innovation has achieved rapid development. In terms of both the total number and types of patents, China's renewable energy innovation is showing a positive trend.

Figures 3 and 4 show the spatial distribution of REI in China from 2006 to 2019, which generally increased in all regions. The maximum value for REI in 2006 was 620, but in 2019, that in most regions was higher than 620—Jiangsu ranked first, while Guangdong, Beijing, and Zhejiang performed well, and among the western regions Sichuan showed outstanding performance. The spatial distribution of REI in China is significantly unbalanced, and the overall performance shows a gradient distribution trend that decreases from east to west and from the coastal to the inland regions.

Geographical distribution of China's renewable energy innovation. This study applies the SDE method and comprehensively analyzes the evolutionary path of the ellipse center as well as the differences in the directional distribution of China's REI from 2006 to 2019. The spatial evolution of China's REI from 2006 to 2019 is shown in Fig. 5. The evolution of the SDE parameters of REI over the 14-year period is presented in Supplementary Table S3.

Fig. 4 Spatial distribution of REI in China in 2019. A spatial distribution description of REI in China in 2019.

Fig. 5 The ellipses of REI in China from 2006 to 2019. A spatial evolution description of REI in China from 2006 to 2019.

Table 3 Global Moran's I of REI in 31 regions of China from 2006 to 2019.

Year	W^{0-1}	W^{g}	W^{e}	W^{ge}
2019	0.159*(1.750)	0.126*(1.900)	0.318***(4.170)	0.364***(3.410)
2018	0.184**(1.989)	0.170**(2.431)	0.301***(3.983)	0.366***(3.446)
2017	0.206**(2.183)	0.162**(2.324)	0.270***(3.609)	0.328***(3.102)
2016	0.278***(2.824)	0.208***(2.856)	0.252***(3.373)	0.345***(3.234)
2015	0.225**(2.330)	0.168**(2.376)	0.271***(3.585)	0.328***(3.077)
2014	0.188**(2.039)	0.111*(1.734)	0.238***(3.258)	0.261**(2.557)
2013	0.191**(2.065)	0.100(1.603)	0.259***(3.514)	0.287***(2.782)
2012	0.212**(2.239)	0.115*(1.765)	0.298***(3.949)	0.308***(2.942)
2011	0.150*(1.663)	0.077(1.301)	0.311***(4.067)	0.262**(2.524)
2010	0.156*(1.672)	0.086(1.375)	0.338***(4.266)	0.298***(2.749)
2009	0.119(1.377)	0.067(1.183)	0.338***(4.369)	0.257**(2.472)
2008	0.113(1.311)	0.083(1.363)	0.360***(4.592)	0.281***(2.658)
2007	0.110(1.328)	0.079(1.361)	0.320***(4.250)	0.250**(2.470)
2006	0.069(1.053)	0.038(0.957)	0.253***(3.824)	0.152*(1.792)

The *t* statistics are in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

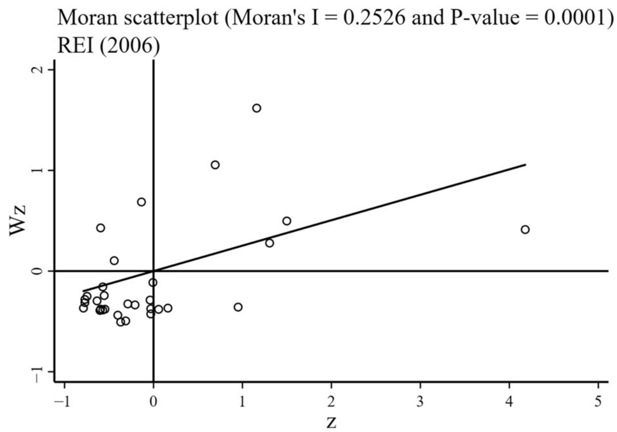

Fig. 6 Moran scatter plot of China's REI in 2006. It shows the spatial relationships among the 31 regions' REI of China in 2006.

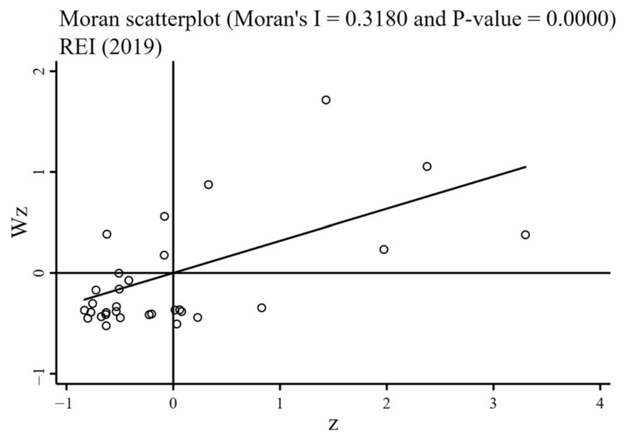

Fig. 7 Moran scatter plot of China's REI in 2019. It shows the spatial relationships among the 31 regions' *REI* of China in 2019.

The changes in the ellipse center in Fig. 5 reveal the trajectory of the renewable energy innovation space. The ellipse center is located at the junction of Henan and Anhui Provinces, which indicates that the REI in the east is generally higher than that in the west. The weighted mean centers moved in a southward direction from Shangqiu in 2006 to Xinyang in 2019, thus indicating that the REI in the southern regions is greater. The overall movement trajectory of the ellipse center from 2006 to 2019 was from north to south, which, coupled with the finding from Figs. 3 and 4 (i.e., that regions with a high REI in China are mainly concentrated in the eastern coastal areas), support **Hypothesis 1**.

Supplementary Table S3 shows the details of ellipses changes. From 2006 to 2019, the long-axis standard deviation decreased from 1000.64 to 921.11 km, which indicates a strengthening of the directional trend. Furthermore, the value of the short-axis standard deviation decreased from 695.27 to 684.58 km, which indicates a weakening of the degree of dispersion. The azimuth value of the SDE represents the main directional trend of the spatial distribution of renewable energy innovation. Its decrease from 40.28° in 2006 to 38.82° in 2019 indicates that renewable energy innovation developed following a clockwise rotation relatively rapidly in the southwest and northeast regions of the ellipse. In addition to the above changes, the center of the ellipse also shifts to the south.

Spatial autocorrelation test. Based on W^{0-1}, W^{g}, W^{e}, and W^{ge}, the global Moran's *I* of REI in 31 regions from 2006 to 2019 is shown in Table 3. Most of the global Moran's *I* value of REI is significantly positive, thus indicating that the spatial distribution of REI in Chinese regions is not random and shows a positive spatial correlation, which means that regions with high (low) levels tend to be adjacent to each other, thus verifying **Hypothesis 2**. The global Moran's I value of REI under W^{e} is the most significant, followed by W^{ge}, W^{0-1} and W^{g}. This spatial correlation is more closely related to regional economic development.

The Local Moran's *I* is used to determine the agglomeration patterns of each region. It can be seen from Figs. 6 and 7 that renewable energy innovation has a significant local spatial agglomeration effect under W^{e}. Specifically, in 2019, Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong were in H–H, thus indicating that these regions with a high REI were surrounded by other regions with a high REI. Anhui, Shandong, Henan, Hubei, Sichuan, and Shaanxi were in H–L, thus indicating that these regions with a high REI were surrounded by regions with a low REI. In addition to regions such as Anhui, Sichuan, and Shaanxi changing from low to high REI levels, the spatial pattern of relationships between neighboring regions did not show significant changes from 2006 to 2019.

Table 4 Decomposition results of the drivers of renewable energy innovation.

Effect	Variable	W^{0-1}	W^{g}	W^{e}	W^{ge}
Direct effect	lnRD	0.333**(2.34)	0.251*(1.75)	0.382***(2.78)	0.383***(2.86)
	lnGDP	0.595***(3.49)	0.260(1.43)	0.669***(3.75)	0.403**(2.20)
	lnREIC	0.026(0.60)	0.017(0.42)	0.054(1.37)	0.044(1.10)
	RES	0.002(0.47)	0.003(0.67)	0.001(0.35)	0.002(0.44)
	lnCO2	0.829***(4.19)	0.722***(3.99)	0.680***(3.83)	0.711***(3.84)
	IPCII	0.142**(−1.98)	−0.153**(−2.21)	−0.158**(−2.19)	−0.165**(−2.36)
Indirect effect	lnRD	0.273(1.49)	0.475**(2.16)	0.174(0.81)	0.324(1.63)
	lnGDP	0.596**(2.37)	0.926***(2.78)	0.187(0.59)	0.732***(2.72)
	lnREIC	0.183**(2.33)	0.131(1.56)	0.361***(2.63)	0.109(1.48)
	RES	−0.002(−0.20)	−0.010(−0.66)	−0.005(−0.31)	−0.006(−0.55)
	lnCO2	−0.775*(−1.86)	−0.622(−1.03)	−0.267(−0.49)	−0.349(−0.78)
	IPCII	−0.430***(−2.87)	−0.530***(−2.81)	−0.242(−1.39)	−0.383**(−2.29)
Total effect	lnRD	0.606***(3.79)	0.726***(3.68)	0.556***(2.65)	0.707***(3.63)
	lnGDP	1.190***(4.98)	1.187***(3.67)	0.857**(2.48)	1.135***(4.20)
	lnREIC	0.209***(2.84)	0.148(1.61)	0.415***(2.84)	0.152*(1.79)
	RES	0.000(0.03)	−0.007(−0.47)	−0.004(−0.21)	−0.004(−0.37)
	lnCO2	0.054(0.13)	0.100(0.17)	0.413(0.75)	0.362(0.81)
	IPCII	−0.571***(−3.62)	−0.683***(−3.46)	−0.400**(−2.21)	−0.548***(−3.00)

The *t* statistics are in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

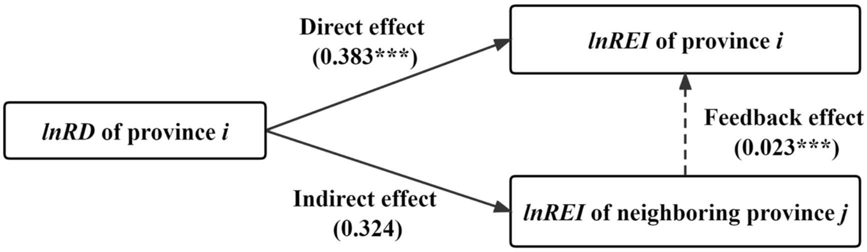

Fig. 8 The direct and indirect effects of lnRD on *lnREI*. It shows the decomposition effects of lnRD on lnREI.

Spatial effect decomposition. Choosing an appropriate spatial panel model is a prerequisite for accurately measuring the spillover effect and driving factors of renewable energy innovation. Following Elhorst (2012), we conduct spatial diagnostic tests for model specifications and present the results in Supplementary Table S4. The results reported in Supplementary Table S4 show that the null hypothesis of both the Wald and the LR tests were rejected for all spatial matrices. Therefore, the SDM model, which incorporates the dual fixed effects of time and space, is more suitable for this study, and the results are shown in Supplementary Table S5. The coefficient of ρ under W^{e} in Supplementary Table S5 is positive at the 5% significance level, while that under the other spatial weight matrices is positive at the 1% significance level, thus indicating that renewable energy innovation has a positive spillover effect, which further supports **Hypothesis 2**.

The decomposition results of the drivers of renewable energy innovation are shown in Table 4. We confirm the existence of a feedback effect in these variables, which influences local renewable energy innovation by affecting that in adjacent regions and returning to the region itself. For example, the direct effect of lnRD is 0.383 (see Table 4) and its coefficient is 0.360 (see Supplementary Table S5); its feedback effect is 0.023, or 6% of the direct effect (see Fig. 8). There is a feedback effect of lnRD, which increases local renewable energy innovation by affecting neighboring regions and returning the results of their progress to the originating region.

Increasing government R&D investment is an effective way to promote China's renewable energy innovation. However, this beneficial effect seems to be confined mainly to the local region. Under four spatial weight matrices, the direct and total effects of lnRD are significantly positive. First, the direct effect of lnRD is 0.383 and is significant at the 1% level under W^{ge}, meaning that a 1% increase in lnRD will, on average, cause the relative growth rate of lnREI to increase by 0.383%. Second, only under W^{g} does the coefficient of the indirect effect pass the 5% significance test. The spillover effect of lnRD is more likely to occur between regions that are geographically closer because it is easier for them to coordinate their R&D strategies and policies to accelerate the flow and agglomeration of innovation resources and thus the spillover of innovation achievements. However, the influence of political networks, the free-riding behavior of firms, and politicized R&D activities due to corruption and rent-seeking may hinder renewable energy innovation in surrounding areas (Gao and Yuan, 2022; Gersbach et al., 2019). Therefore, the spillover effect of lnRD is not obvious. Finally, the total effect of lnRD passes the 1% significance level test, thus indicating that public R&D investment is an important driver of renewable energy innovation. The above analysis shows that **Hypothesis 3a** is verified.

Under four spatial weight matrices, the direct, indirect, and total effects of the economic base (lnGDP) are significantly positive, thus indicating that economic development is an important driver of renewable energy innovation. This is consistent with Gao and Yuan (2022). First, the direct effect of lnGDP is 0.403 under W^{ge} and significant at the 5% level, which implies that a 1% increase in lnGDP will, on average, cause the relative growth rate of lnREI to increase by 0.403%. Second, the indirect effect of lnGDP is significantly positive under W^{ge}. With the deepening of regional economic integration, the in-depth integration of markets, policies, and other factors between regions will inevitably lead to the coordinated development of provincial renewable energy innovation. In addition, the indirect effect of lnGDP is about 1.8 times the direct effect, which suggests that the strong spillover effect cannot be ignored. Finally, under the significantly positive direct and indirect effects, the total effect of lnGDP is positive. The above analysis shows that **Hypothesis 3b** is verified.

Notably, under four spatial weight matrices, none of the direct effects of lnREIC are significant, and the direct, indirect, and total effects of RES are not significant. However, the direct effects of lnCO2 are all significantly positive, and the indirect effect of lnCO2 is negative and statistically nonsignificant. Most direct, indirect, and total effects of IPCII are significantly negative, which may indicate that more targeted environmental regulations can promote renewable energy innovation.

Robustness test. Schleich et al. (2017) demonstrated that patent stock could more accurately capture the sector-specific effects, such as technology suppliers' learning-by-inventing. Hence, we conducted a robustness test using the stock of renewable energy patents as the dependent variable, in which the depreciation rate is 15% (Lin and Chen, 2019). Furthermore, the effects usually take a time lag considering the patent authorization requires some time. Therefore, we conducted a regression with lagging first-order explanatory variables. Both of them prove that the conclusions are robust. The estimated results are shown in Supplementary Table S6.

The presence of the spatially lagging dependent variable in Eq. (1.11) implies that ordinary least squares estimates will be biased and inconsistent since the spatial lag is mechanically correlated with the disturbance term. There will also be omitted variables that could potentially bias our results. To address these issues, we change the estimation method to use the generalized spatial two-stage least squares (GS2SLS) by Kelejian and Prucha (1998) in the spatial model Eq. (1.11) without spatially lagging the independent variables. The instrumental variable (IV) we use is a bundling of $\boldsymbol{WX}$ and $\boldsymbol{W}^2\boldsymbol{X}$, where $\boldsymbol{W}$ is the weight matrix, $\boldsymbol{W}^2$ is the second spatial lag, and $\boldsymbol{X}$ is the independent variable matrix.

In addition, since innovation is a continuous process, and the accumulation of innovation in the previous period can attract more R&D funding or create more favorable R&D conditions for the current innovation activity, we introduce the first-order lag term of REI to establish a dynamic SDM model based on Eq. (1.11), which also can also alleviate the problem of omitted variables. To further address endogenous problems, the generalized moment method (GMM) by Han and Phillips (2010) is used to estimate the dynamic SDM model. Both results of GS2SLS and GMM remain robust. The estimated results are shown in Supplementary Table S7.

Discussion

Spatiotemporal pattern of renewable energy innovation. Most regions in H–H of Figs. 6 and 7 are located in the eastern coastal area, where the economy is highly developed with comparatively advanced industrial structures. By comparison, most regions in L–L are located in western and northeastern China, where renewable energies are abundant but the economic activity is energy intensive. Therefore, China exhibits a spatiotemporal character such that the high-REI regions are mainly located in the eastern coastal area and the low-REI regions are mainly located in western and northeastern China. The main reasons for this finding are as follows. (i) The reform and opening-up policies have provided an inexhaustible motivating force for economic development in the southeastern coastal provinces. Jiangsu, Zhejiang, and Guangdong are among the most economically productive provinces in China and provide ample support in terms of scientific research and capital investment in local renewable energy innovation (Li et al., 2022). (ii) The power grid in the northern region is underdeveloped, and its power transmission is limited (Yang et al., 2020b), which is not conducive to the consumption of renewable electricity and thus detracts from the application of innovative technologies. (iii) There is an agglomeration effect of innovation. China's industrial agglomeration areas are mainly distributed in the eastern regions, such as the Yangtze and Pearl River Deltas. The flow of innovation elements in agglomeration areas can produce a knowledge spillover effect, which in turn improves the region's overall innovativeness.

Spillover effects and influencing factors. According to **Hypothesis 2**, renewable energy innovation can yield a stronger spillover effect between regions that are geographically closer to each other and have similar levels of economic development. The reason for this phenomenon is that since 2012, the Chinese government has continued to increase funding for sustainable development and environmental quality (Karplus et al., 2021). In 2014, what has been described as the most stringent environmental protection law in China's history was promulgated by the Ministry of Ecology and Environment (MEE, 2014), which placed a greater emphasis on the environmental governance responsibilities of local governments. Local government officials have a strong intrinsic motivation to mimic the low-carbon behaviors of geographically and economically adjacent provinces and promote renewable energy innovation to improve environmental quality. Nonetheless, it remains unclear how can renewable energy innovation can be effectively promoted in China.

Although increasing government R&D investment is an effective way to promote China's renewable energy innovation, this beneficial effect seems to be limited to the local region. That is, there is only a direct effect. Public R&D funding can mitigate the inefficiencies caused by market failures and provide a useful supplement to the technological innovation investments of private enterprises. However, government support is unsustainable, and policies can only play an important role in the early stages of renewable energy development (Johnstone et al., 2010; Pitelis et al., 2020). As the renewable energy industry continues to grow, its drivers will shift, and market-oriented policy support will become crucial. The Chinese government is currently vigorously promoting the development of green finance, such as green bonds and ESG investment, to actively expand the financing channels for the renewable energy industry.

The more developed the economy, the stronger its willingness to commit to renewable energy innovation will be. With the deepening of regional economic integration, the in-depth integration of markets, production factors, policies, and development strategies between regions continues to advance and will inevitably lead to the coordinated development of renewable energy innovation among provinces, which will enhance the spillover effect. That is, economic development has not only a direct effect but also an indirect effect. Therefore, deepening cooperation and coordinated development in key regions such as the Beijing–Tianjin–Hebei region and the Yangtze River Delta are effective ways to enhance renewable energy innovation. In particular, for the western region, which is characterized by relatively backward economic development, forming economic agglomeration areas can also promote renewable energy innovation.

There are other factors that do not currently have a significant impact on renewable energy innovation at the provincial level in

China, such as installed renewable energy capacity and the proportion of renewable electricity in the total electricity supply. The insignificance of these two factors implies that renewable energy innovation is not necessarily positively correlated with renewable energy consumption and abundant resource endowments, which further explains why the spatial distribution of renewable energy innovation shows a trend that is opposite to that of resource distribution in China but is highly correlated with its economic distribution.

It should be noted that our analysis only focuses on the development of renewable energy in China at the current stage, and as it enters large-scale adoption, the factors influencing innovation may undergo a major shift such that the role of government diminishes and the role of the market becomes stronger. However, the spatial agglomeration effect will still play an important role for the foreseeable future.

Conclusions and policy implications

Conclusions. Based on province-level panel data from 2006 to 2019, which includes 31 regions in mainland China, this study explores the spatiotemporal pattern and drivers of renewable energy innovation. We obtain the following findings.

First, renewable energy innovation shows distinct spatial differences and aggregation characteristics among China's provinces. The Beijing–Tianjin–Hebei region, the middle and lower reaches of the Yellow River, and the middle and lower reaches of the Yangtze River are the main agglomeration areas of renewable energy innovation. In terms of the weighted mean centers of SDE, renewable energy innovation shows a trend of being strong in the east and south and weak in the west and north, and the latter trend is becoming more significant owing to the fact that the southeastern region has experienced rapid economic development. Second, the Global Moran's I increase from 0.152 in 2006 to 0.364 in 2019, which shows a positive spatial correlation of renewable energy innovation. It can be seen from the results of the local Moran's I test that China formed high innovation level clusters mainly in the eastern coastal area and low innovation level clusters mainly in the western and northeastern areas. Furthermore, the pattern of the spatial distribution exhibits spatial locking and path dependence. Third, the favorable impact of government funding on innovation is mainly observed in the local area, while GDP per capita helps boost innovation for the local as well as the neighboring regions. Renewable energy capacity has an obvious spillover effect, while the proportion of renewable energy power generation did not play a role in innovation during the research period. The total effect of CO_2 emissions is limited because the effects show diametrically opposite directions within and outside the region, while investments in industrial pollution control inhibit innovation in all regions.

Policy implications. Based on the above analysis, the following policy implications are proposed.

First, attention should be paid to the less developed areas in the western regions and renewable energy innovation should be promoted more aggressively in northern China. As the results show, although western China has abundant renewable resources in the form of hydro and solar energy, it lagged behind in terms of technological development and the innovation center gradually shifted from the north to the south. To balance the geographic distribution of renewable energy innovation, eastern China, which has strong research platforms and renewables-related enterprises, can focus on research and development to be the primary source of renewable energy innovation and thus the spillover of knowledge and talent. For the regions in western and northern China with weak innovation capabilities, we consider the fact that renewable energy innovation in neighboring provinces has been shown in our analysis to have a positive spillover effect on local provinces and recommend that governments build on their resource and cost advantages by introducing new technologies and equipment to create a more mature renewable energy market, which will in turn further attract new technologies and equipment, thus forming a virtuous circle. For example, according to the recently released *Implementation Plan for Promoting the High-quality Development of New Energy in the New Era* promulgated by the National Development and Reform Commission and National Energy Administration (NDRC, NEA, 2022), the central government will promote the construction of large wind power and photovoltaic bases in the Gobi desert and other desert areas, which are mainly concentrated in western China.

Second, increased government funding of R&D investment should result in sustained economic growth and expansion of the installed renewable energy capacity. The results show that R&D investment can effectively stimulate renewable energy innovation, although this effect is limited to the local area, while economic development and installed renewable energy capacity have spillover effects. In light of these implications, economic development should be further promoted and the renewables industry should be further expanded. Furthermore, collaborative innovation activities between enterprises and research institutions in different regions should be encouraged to create spillover effects in neighboring regions.

Third, market-oriented R&D investment should also be promoted. The government can increase its support for new energy projects through green bonds and green credit and by including new energy projects in pilot real estate investment trusts. Furthermore, the certified GHG emissions reduction of qualified new energy projects can be included in the national emissions trading market to offset quotas. It is worth noting that the government's innovation policy should avoid allocating funding to specific enterprises but rather create an environment that encourages fair competition through targeted and inclusive policies to allow market mechanisms to guide the allocation of innovation factors.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Notes

1 Municipalities include Beijing, Tianjin, Chongqing and Shanghai.
2 Autonomous regions include Inner Mongolia, Ningxia, Qinghai, Tibet, and Guangxi.

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