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RESEARCH ARTICLE

Research on the impact of energy technology innovation on total factor ecological efficiency

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Abstract
Promoting sustainable economic development from the perspective of energy technology is crucial, given limited energy resources and severe environmental pollution. Based on the panel data of China's provinces from 2000 to 2017, we empirically explore the complex relation among energy technology innovation, regional economic growth, and total factor ecological efficiency. We innovatively introduce ecological footprint as one of the input indicators of total factor ecological efficiency measured using slack-based measure–data envelopment analysis, thereby comprehensively quantifying sustainable economic development. Moreover, we adopt spatial econometric and threshold regression models to empirically assess the relation between energy technology innovation and total factor ecological efficiency. We infer the following conclusions. First, both China's provincial ecological efficiency and energy technology innovation possess significant spatial positive correlation, manifesting a spatial geographical distribution agglomerated by similar characteristics. Second, the regional energy technology innovation has a remarkable spatial effect on ecological efficiency, displaying a U-shaped trend. Compared with the direct effect, the spatial spillover effect is more intense, along with a much stronger long-term influence. Third, under the regulation of regional economic growth, two inflection points exist in the effect of energy technology innovation on ecological efficiency. Energy technology innovation is not conducive to total factor ecological efficiency under low regional economic growth. No significant relation exists between the two core variables under medium regional economic growth. Furthermore, energy technology innovation positively influences total factor ecological efficiency only when regional economic growth reaches a certain peak.

Keywords Energy technology innovation · Total factor ecological efficiency · Ecological footprint · Sustainable economic development · Spatial Durbin model · Panel threshold model

Introduction

In 2015, the United Nations adopted the '2030 Agenda for Sustainable Development', which outlined 17 Sustainable Development Goals (SDGs), ensuring an ideal balance among society, economy, and environment (Guan and Xue 2019). Of these goals, SDG12 proposed sustainable consumption and production patterns and emphasised improving resource efficiency and identifying economic and ecological benefits (Fonseca et al. 2020), thereby highlighting the critical issues of green economy and sustainable development. Currently, ecological environmental degradation poses a potential threat to economic security and social stability. This degradation has resulted from massive mining and utilisation of fossil fuels as well as pollution emissions due to energy consumption, which have increasingly exceeded the environmental carrying capacity (Xu et al. 2019). In this context, accelerating sustainable development has become a global challenge. Being the world's largest energy producer, consumer, and carbon (CO2) emitter, China should shoulder more responsibilities than other developing countries (Lin 2019). At the 75th session of the United Nations General Assembly in September 2020, Chinese President Xi Jinping

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vowed to make every effort to peak CO2 emissions by 2030 and strive for CO2 neutrality by 2060. This is an integrated approach to ensure the coordinated progress of China's economy and ecosystem as well as an ambitious goal of China towards becoming a world power in green development.

An innovation-driven systemic transformation of energy is pivotal for achieving 'carbon neutrality' by 2060 as well as sustainable development and 'green recovery' in the post-epidemic period (An 2020). SDG7 proposed that access to affordable and clean energy is crucial for green development (Nerini et al. 2018). Clean energy technologies such as renewable energy and energy efficiency, in addition to advanced and cleaner fossil fuel technologies, are essential for the coordinated development of ecological civilisation and economy. Theoretically, energy technology innovation is considered a powerful means to coordinate economic growth and low-CO2 emission reduction (Tang et al. 2020). However, given the varied levels of regional economic development in China, this coordination role has undergone subtle changes (Yan et al. 2020). In addition, as a technological element, energy technology is considered a non-competitive public good, accompanied by 'energy technology diffusion' and 'energy technology spillover'. Therefore, we should comprehensively consider the role of spatial overflow characteristics. Accordingly, the question posed pertains to the effect of energy technology innovation on green development when including the space factor.

We thus decided to use the spatial econometric and threshold regression models to conduct empirical research in order to explore the aforementioned issues. Based on the provincial data of China from 2000 to 2017, we profoundly examined the spatial and non-linear effects of energy technology innovation on total factor ecological efficiency. We can infer the following four marginal contributions: (1) with regard to the definition of energy technology innovation, we included the exploitation and application of renewable energy in previous studies. We also introduced the targeted goals of energy saving and emission control of traditional fossil fuels into the research framework of energy technology innovation. The comprehensive definition effectively adapts to the current status of China, which is in the energy transition stage, and provides a profound reference for other developing countries in the period of energy transition. (2) The original energy input is substituted by the regional ecological footprint, measured using the advanced ecological footprint approach. Accordingly, the measurement of total factor ecological efficiency encompasses multi-dimensional factors such as labour, capital, ecology, energy, pollution output, and economic output, which reflect the evolution and current situation of the coordinated development of regional ecological economy across the board. (3) We considered the spatial spillover characteristics of technological innovation. We thus adopted the spatial measurement model to innovatively incorporate spatial factors into the relation between energy technology innovation and total factor ecological efficiency to mainly discuss the spillover effect using the dynamic spatial Durbin model. (4) Based on the unbalanced regional economic development in China, we assessed the effect of the regional heterogeneity of energy technology innovation on regional total factor ecological efficiency using the threshold model to more accurately examine the non-linear relation between the two.

The rest of the paper is organised as follows: the 'Literature review' section presents the relevant literature on the relation between energy technological innovation and economic growth, the relation between energy technological innovation and environmental performance, and total factor ecological efficiency. The 'Theoretical analysis and research methods' section provides the theoretical basis and research hypothesis of this paper. It also presents the construction of two econometric models. The 'Empirical analysis of the effect of energy technology innovation on TFEE' section presents the empirical results of two econometric models. The 'Discussion' section indicates the similarities of and differences between the results in this study and those in the existing literature and conducts an in-depth analysis of the findings. Finally, the 'Conclusions and suggestions' section summarises the main conclusions and proposes relevant policy suggestions.

Literature review

Sustainable development is a high balance between natural resources and economic development; in other words, it implies the maximisation of net the benefits of economic development while ensuring the supply of natural resources and environmental privilege (Zhang 1997; Ding et al. 2020). Many scholars have considered total factor ecological efficiency as an essential indicator to measure sustainable economic development (Shen et al. 2020). Similarly, as a knowledge-intensive factor, energy technology innovation can induce the factor substitution effect and facilitate energy conservation and emission reduction, essential for economic growth and environmental protection. Therefore, this paper reviews the relevant literature from three aspects: relationship between energy technology innovation and economic growth; relationship between energy technology innovation and environmental performance; and total factor ecological efficiency.

Research on the relation between energy technology innovation and economic growth

Academia has exclusively focused on the relation between energy technology innovation and economic growth. With varied historical backgrounds, multiple definitions of energy technological innovation make the existing conclusions concerning the effects of energy technological innovation on economic growth different. Therefore, identifying the economic growth effects becomes essential, given the varied definitions of energy technology innovation (Tawney et al. 2015). Sagar (2002) proposed that energy technology innovation includes two parts: (1) the emerging and substitutable energy technology and (2) the improvement of the original traditional energy technology. Previously, scholars have focused more on technological innovations in the development and utilisation of fossil energy. The scholars believed that such innovations could serve people's lives and production activities as well as promote economic growth (Shao et al. 2021). Based on the panel data of China from 1965 to 2004, Guo (2007) conducted an empirical study by using the vector autoregression (VAR) and vector error correction models and found that traditional energy inputs incorporating technological factors have negatively affected China's economy. Linton (2017) argued that the low stock of energy technology in China is the main reason for ineffective eradication of the effects of energy consumption externalities on economic growth.

Notably, scholars have re-examined the connotation of energy technology innovation and shifted their focus towards low-CO2 energy technology, given the background of environmental protection and green development. Guo et al. (2016) discussed the relation between energy technology innovation and economic growth from the perspectives of low-CO2 energy technology innovation policy, investment, capacity, and organisation. The authors determined that low-CO2 energy technology positively affects economic growth by enhancing the energy consumption structure and promoting investment in resources and wealth. According to IPC Green Inventory, low-CO2 energy technology encompasses seven types of technical topics, with alternative energy production and energy conservation technologies being the most concerning types (Zhang and Geng 2021). Magnani and Vaona (2013) conducted an empirical analysis of the spillover effect of renewable energy technology in Italy and demonstrated that renewable energy technology considerably promoted regional economic growth. Following the Laspeyres decomposition-based analysis of China's green transition of the industrial economy, Wu (2017) held that the clean energy technology innovation mainly determined China's green economic growth. The role of clean energy technology innovation was more prominent than those of energy structure adjustment and environmental effects of new energy. Sun et al. (2020) considered the environmental Kuznets curve hypothesis and explored the long-term relation between regional economic growth and renewable energy technology in China. The authors deemed that renewable energy technological innovation would increase the economic growth level in the long run. With regard to energy-saving technology innovation, Qian (2019) adopted the three-stage least square method and concluded that independent innovation in energy technology could positively affect economic growth. Kamoun and Abdelkafi (2020) examined the effects of energy-saving technology innovation on a series of macroeconomic variables and affirmed its beneficial effects on economic growth.

Research on the relation between energy technology innovation and environmental performance

The existing research on the relation between energy technology innovation and environmental performance mainly focuses on two aspects: CO2 emissions and green economic development. According to Böhringer et al. (2020), fields such as energy development, utilisation, and consumption involved in energy technology often highly correlate with CO2 emissions. From the perspective of environmental pollution, research on energy technology innovation and CO2 emission has laid a sufficient foundation for further research. Furthermore, green economic development, which closely combines environmental conditions with economic development, is a more in-depth research perspective in the current research on energy technology innovation.

Most scholars have considered the emission reduction effect of energy technology innovation. Altıntas and Kassouri (2020) considered the European countries as the sample. Based on the data on energy R&D and carbon footprint, linear and non-linear models were built separately. The results revealed that from 1985 to 2016, energy technology innovation in European countries effectively curbed carbon footprint reduction. Ali et al. (2020) considered carbon emitters from 1990 to 2017 and indicated a stability relation between CO2 emissions and environmental technology in the long run. The effects of energy technology innovation on CO2 emissions differ with the type of energy technology used. Wang et al. (2012) constructed a dynamic panel model based on China's provincial data and explored the relation between varied types of energy technology patents and CO2 emissions. They determined that fossil energy technology patents did not considerably affect CO2 emissions. Furthermore, they concluded that carbon-free energy technology patents significantly curbed the increase in CO2 emissions. In addition, regional disparities existed in the emission reduction effects of renewable energy technology innovations. Wang et al. (2012) conducted a subregional regression analysis and further discovered that the emission reduction effect of clean energy technology innovation was more significant in eastern China and indicated no apparent effects in the central and western regions. Similarly, Cheng and Yao (2021) concluded that the emission reduction effect of renewable energy technology innovation was more evident in eastern China; however, they argued that renewable energy innovations would reduce CO2 emissions only in the long run.

Scholars have affirmed the positive effects of energy technology innovation on green economic development (Kirikkaleli and Adebayo 2020). Notably, specific differences have been observed in the effects of energy technology innovation on green economic development in different regions owing to the diversity of resource endowment and development status in regions, including consumer preference, regional consumption structure, energy patent structure, and income level. In other words, the effects of energy technology innovation on green economic development are regionally heterogeneous. Specifically, Zhang et al. (2015) indicated an inverted U-shaped non-linear relation between energy technology innovation activities and green economic growth because of differences in regional residents' consumption preferences. Energy-saving technological advances can effectively reduce energy consumption only in regions where consumers are patient and marginal utility elasticity is smaller than one. Zhang et al. (2019) conducted empirical research on the sample data of inland provinces in China using the VAR model. The authors revealed that energy technology patents positively correlated with the coordination degree of regional ecological construction. The energy technology innovation played a more significant role in energy saving and consumption reduction because the central and northern parts of China consumed a large amount of coal resources and mainly developed fossil energy patents. Ley et al. (2016) demonstrated that the bidirectional externality of energy technology innovation would result in free-riding behaviour. Such externality would ultimately affect the application and promotion of technology innovation in poor areas and its beneficial influence on green development. Yan et al. (2020) established the partial linear norm function model and investigated the effects of technology innovation on sustainable energy and green total factor productivity growth at varied income levels. The authors confirmed that renewable energy technology innovation can play a role in total factor ecological efficiency only if the standard of regional income level exceeded a critical point. Once the income level passes the turning point, the total factor ecological efficiency would follow the same trend as that of the income level.

Research on total factor ecological efficiency

Sustainable development remains unachievable without enhancing environmental quality, which requires focus on ecological efficiency (Zafar et al. 2020). Ecological efficiency symbolises the coordination degree between economy and ecological environment, usually represented by the proportion of economic benefit of productive outcomes to the ecological impact (Schaltegger et al. 1990). Compared with single factor energy efficiency measured by resource depletion per unit of the gross domestic product, total factor ecological efficiency is unique as it contains various input and output factors. Input indicators include labour, capital, energy, and ecology. Output indicators usually include desirable output (economic development level) and undesirable output (environmental pollution). Therefore, total factor ecological efficiency is the ideal choice to systematically and comprehensively estimate green economic development under the demand of sustainable development (Li and Hu 2012). Accordingly, scholars have measured total factor ecological efficiency using varied methods and have obtained different results, concluding the status quo of the energy–environment–economy system and its improvement path (Wang et al. 2017).

Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are considered star approaches for measuring total factor ecological efficiency. He et al. (2017) used SFA to propose the potential for regional energy saving and pollution reduction in China after evaluating environmental efficiency in various regions. Nevertheless, compared with SFA, DEA can include undesirable outputs represented by environmental impacts into the research system and distinguish the independent effects of efficiency changes and technological progress. Previous studies have analysed total factor ecological efficiency from the perspectives of labour, capital, and energy resource input (Wang and Zhang 2016). Recently, few scholars have considered ecological input for sustainable development and replaced simple energy consumption with ecological footprint, thereby assessing a more accurate status quo of regional ecological efficiency and ecological pressure in China (Shi and Wang 2016). Tang et al. (2021) documented that with the rapid economic and social development, renewable and non-renewable resources have gradually become a key factor restricting economic growth.

Previous scholars have only considered fossil energy such as coal and oil as input indicators of natural resources, not adequately representing all types of natural resources. Ecological efficiency measured using such input indicators is likely to be 'partial factor ecological efficiency'. Wackernagel and Rees (1996) defined ecological footprint as the total land area consumed by resources, characterising the extent of human consumption of resources and waste generated by humans. Ecological footprint encompasses non-renewable natural resources such as oil and natural gas as well as renewable natural resources such as forests and fishery. Of the existing indicators of natural resources, ecological footprint can more comprehensively describe natural resources and reflect ecological consumption.

Scholars have documented numerous factors influencing total factor ecological efficiency from multiple perspectives. These factors include economy scale (Chen and Golley 2014), industrial structure (Lin and Du 2015), technological progress (Yang et al. 2017), technological innovation

(Cai and Zhou 2017), and so on. Chen (2016) and Wu and Du (2018) conducted an empirical analysis of China's provincial and regional data and concluded that technological progress and technological innovation are vital to enhance total factor ecological efficiency and ensure a sound ecological construction. Ghisetti and Quatraro (2017) held homologous views, believing that green technology innovation and energy technology innovation facilitate regional green economic gain and sustainable development.

Existing research on energy technology innovation and total factor ecological efficiency provides the theoretical basis for this paper. However, there remains scope for improvement in the previous literature. First, existing theoretical research believes that the concept of energy technology innovation is multi-dimensional. However, empirical research on energy technology innovation lacks a careful consideration of energy technology innovation. Scholars have focused only on a single type of energy technology innovation, such as renewable energy technology innovation or energy-saving technology innovation. Few scholars have simultaneously considered the emerging alternative energy technology and the improvement of the original traditional energy technology as research objects. Second, the definition and measurement of total factor ecological efficiency principally began with the input and output indexes. Only factors such as labour, capital, and energy were considered input indicators, with few scholars including ecological footprint in the research framework (Xing et al. 2018). None of the studies has examined the relation between energy technology innovation and green economic growth from the perspective of ecological consumption. Thirdly, existing research has primarily affirmed the spatial distribution characteristics of total factor ecological efficiency (Lin et al. 2017). As a technological element, energy technological innovation may have the common spatial spillover effect of technological innovation activities. However, a certain gap exists in the research on the spatial effects of energy technology innovation on total factor ecological efficiency. Lastly, existing research on the relation between energy technology innovation and total factor ecological efficiency lacks conventional non-linear test analysis using the threshold model. Only some scholars have initially obtained regional differences in the relation between the two through VAR and dynamic panel models.

Theoretical analysis and research methods

Theoretical analysis

Analysis of the spatial effect of energy technology innovation on total factor ecological efficiency

Since the emergence of endogenous growth models of Romer and Lucas, a technological element's vital function of economic growth remains unassailable. As a branch of technological factor, energy technology innovation has become an influencing factor for regional total factor ecological efficiency (Liao et al. 2020). Under the technological system centred on energy technology, production and consumption indicate a trend towards green and low-carbon production. On the one hand, energy technology innovation has optimised energy development, production, and circulation. Enterprises can reduce energy consumption per unit of output by extending the service efficiency of energy equipment and relaxing energy management, thereby enhancing the efficiency of resource allocation. On the other hand, the promotion and application of new energy, renewable energy, and other emerging technologies can effectively reduce pollution emissions and develop a green economy by improving the energy consumption structure. Such a measure can help reduce pollution emissions without affecting the economic output (Wang and Zhu 2020).

The spatial externalities of technology have been well documented (Marshall 1890; Romer 1986). The flow of energy technology elements is profit-seeking, leading to the transfer and circulation between regions in geographical space. Based on the interactive idea of geospatial innovation in innovation geography, energy technology innovation can considerably affect regional total factor productivity. This effect may result from the inter-regional flow of innovative talents, inter-regional trade and investment of energy innovation achievements, inter-regional mobility, transfer of energy innovation knowledge, and the complementarity of regional innovations (Zhang and Geng 2021). Nevertheless, spatial influence determined by geographical distance, regional technology stock movements, and the level of regional development may not be beneficial (Ullman 1957; Caniëls 2000; Zhou and Peng 2019).

First, Ullman's (1957) spatial interaction theory claimed that spatial interaction exerted by energy technology innovation may follow the 'distance attenuation law'. Based on the first law of geography, geographical proximity and spatial distance between regions affect spatial demand for the flow of energy technology innovation elements. Furthermore, these aspects significantly affect flow costs, such as transportation costs, thereby making a difference to the spatial flow efficiency of energy technology elements. Second, based on the spatial knowledge spillover model of Caniëls, regional knowledge stock primarily results in technology spillover effect—an inflection point of technology stock gap changes the technology spillover effect from positive to negative (Caniëls 2000). As a direct reflection of the regional green technology stock, the agglomeration of energy technology innovation widens the gap of knowledge stock between regions, making the absorption capacity of external regions relatively weak.

This gap is not conducive to the spillover and absorption of energy technology (Roper and Hewitt-Dundas 2015). With the narrowing of the gap of green technology stock between regions (i.e. when regional collaborative energy technology innovation reaches a certain level), the positive effect of technology spillover enhances the total factor productivity of external regions. Third, the increasing pole theory posits that in the initial phase of energy innovation, regions with higher energy innovation capacity more likely agglomerate and preferentially form ‘economic growth poles’ (Perroux 1950). In this process, the factor attraction’s polarisation and siphon effects are not conducive to increasing regional total factor productivity (Luo et al. 2020). Nevertheless, in the long run, with the rise of national energy technology innovation level, the diffusion of inter-regional energy technology will make up for the disadvantages of profit-seeking factors and exert a beneficial trickle-down effect on disadvantaged areas. Such diffusion will boost the green economy in external areas (Hirschman 1958; Zhou and Peng 2019).

Accordingly, we formulate Hypothesis 1: Energy technology innovation has a U-shaped spatial spillover effect on regional total factor ecological efficiency.

Analysis of the non-linear relation between energy technology innovation and total factor ecological efficiency

Favourable economic development conditions can provide sufficient financial support, an R&D environment, and policy support for technological innovation (Wang et al. 2021a, b). However, the effects of energy technology innovation on regional total factor ecological efficiency may differ due to the imbalance of regional economic development in China caused by the natural geographical environment and human characteristics.

According to the infrastructure lock-in effect, the application and popularisation of energy technology in regions with backward economic growth is subject to institutional constraints such as technological system, social system, and political system (Geels and Kemp 2007). Energy technology may fall into the ‘chicken or egg’ paradox due to inadequate energy supply and consumption infrastructure construction, making large-scale development difficult. In addition, based on the ‘Valley of Death’ hypothesis, market stability and investment environment are widely divergent in regions with different levels of economic growth, leading to different prospects and risks concerning the promotion of energy technology innovation products. The application of some energy technology innovation products may fall into ‘Valley of Death’ wherein the capital chain is broken (COMMITTEE ON SCIENCE, U.S. HOUSE OF REPRESENTATIVES 1999). Based on these facts, energy technology innovation may fail to achieve the expected effect of energy conservation and emission reduction as well as hinder regional economic development and the improvement of total factor ecological efficiency. In regions with higher economic growth levels, people’s pursuit of green production and living mode and the government’s sufficient support for ecological construction may promote energy technology innovations and provide a good market environment for the application and transformation of innovation results. These aspects highlight the positive effect of energy technology innovation on total factor ecological efficiency.

In fact, the environmental Kuznets hypothesis can facilitate the regulation of economic growth level with regard to the relation between energy technological innovation and total factor ecological efficiency. Based on the inverted U-shaped relation between the economic growth level and CO_2 emissions (Fan and Sun 2020), when the level of economic growth is low, the emission reduction effects of energy technology innovation have not been fully utilised and CO_2 emissions are still on an upward trend, which are not conducive to ecological efficiency. When the level of economic growth is high, CO_2 emissions significantly decline. In this process, energy technology is likely to give full play to the effects of energy conservation and emission reduction as well as the effect of factor substitution.

Considering the previous analysis, we propose Hypothesis 2: With the increase of the threshold variable represented by the regional economic growth, the effect of energy technology innovation on regional total factor ecological efficiency presents a trend from negative to positive.

Research methods

Spatial econometric model

With the inter-regional flow of production factors such as capital and labour, the barriers between regions are gradually broken. Factor flow will inevitably produce a spatial spillover effect in the close spatial correlation, which is an essential feature of technological innovation. Due to knowledge flow and technology exchange among regions, a significant spillover effect of energy technology innovation is expected (Bai and Jiang 2015). Moreover, total factor ecological efficiency may also be spatially correlated (Chen and Tang 2019). Therefore, we explored the spillover effect of energy technology innovation on total factor ecological efficiency using a spatial econometric model.

First, we constructed a general spatial econometric model—spatial panel Durbin model (Anselin and Griffith 1988).

$$Y_{it} = \rho W * Y_{it} + \beta X_{it} + \theta W * X_{it} + \mu_{it}, \tag{1}$$

where Y denotes the column vector of total factor ecological efficiency ($TFEE$) in different regions for each year.

Following the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework, widely used in environmental economics (Ehrlich and Holdren 1971; Rosa and Dietz 1998), we chose energy technology innovation (*lnET*) as a variable to measure technological level and population density (*POP*) and capital affluence (*CAP*) to represent population factors and regional affluence, respectively. In addition, due to the increasing number of factors affecting total factor ecological efficiency, we included environmental regulation (*REG*) and openness to the outside world(*FDI*). In Eq. (1), X denotes a matrix comprising core variable $l\ nET$, quadratic item, and control variables such as $P\ OP$, CAP, REG, and FDI. $W* Y_{it}$, and $W * X_{it}$ represent interaction effects in spatial metrology (i.e. endogenous interaction and exogenous interaction effects). Furthermore, ρ denotes the spatial autoregression coefficient, and μ represents the error term. Additionally, two parameter column vectors β and θ have to be estimated.

Second, we determined the specific type of spatial measurement model through statistical testing. When $\theta = 0$, it is the spatial lag model (SLM); when $\theta = -\rho\beta$, it is the spatial error model (SEM).

Finally, we established the dynamic spatial panel (Eq. (2)) and decomposed spatial effects to obtain various effects in the short and long term (Elhorst 2014), as indicated in Eqs. (3) and (4).

$$Y_{it} = \tau Y_{it-1} + \varphi W * Y_{it-1} + \rho W* Y_{it} + \beta X_{it} + \theta W * X_{it} + \mu_{it} \tag{2}$$

$$\left[\frac{\partial Y}{\partial x_{1k}}, \cdots, \frac{\partial Y}{\partial x_{Nk}}\right]_{short} = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix} = (I - \varphi W)^{-1}(\beta_k I_N + \theta_k W) \tag{3}$$

$$\left[\frac{\partial Y}{\partial x_{1k}}, \cdots, \frac{\partial Y}{\partial x_{Nk}}\right]_{long} = \begin{bmatrix} \frac{\partial y_1}{\partial x_{1k}} & \cdots & \frac{\partial y_1}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_N}{\partial x_{1k}} & \cdots & \frac{\partial y_N}{\partial x_{Nk}} \end{bmatrix} = [(1-\tau)I - (\varphi + \rho)W]^{-1}(\beta_k I_N + \theta_k W) \tag{4}$$

According to Elhorst (2003), the time lag term Y_{it-1} and spatial lag term $W * Y_{it-1}$ of the total factor ecological efficiency are further added so that both long-term and short-term effects of regional total factor ecological efficiency could be measured. Moreover, the effects of potential factors not included in the econometric model can also be tested.

Threshold model

In this study, we adopted a panel threshold regression model (Hansen 1999) to determine the threshold effect between energy technology innovation and total factor ecological efficiency. As an econometric model of non-linear relation test, panel threshold regression model can accurately calculate the threshold value and verify the significance of endogenous 'threshold characteristics'. Therefore, a single threshold model is established as follows:

$$\begin{aligned} TFEE_{it} = \mu_i + \omega_1 lnET_{it} \times I\left(lnpGDP_{it} \le \gamma\right) + \omega_2 lnET_{it} \\ \times I\left(lnpGDP_{it} > \gamma\right) + \omega X_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

In Eq. (5), the meanings of the dependent, core explanatory, and control variables are same as above. Drawing on Wang et al.'s (2021a, b) research, the threshold variable is expressed by economic growth (*lnpGDP*); ω denotes the specific coefficient matrix, and γ denotes the threshold value. The equation also contains an index function $I(\bullet)$, whose value is 1 when the corresponding condition holds true and is 0 otherwise. $\varepsilon_{it} \sim idd(0, \delta^2)$ denotes the random interference term. Moreover, once the model passes the double threshold test, the following equation can be set up.

In the aforementioned equation, $\gamma_1 < \gamma_2$, and the meanings of other indicators are consistent with that of Eq. (5).

$$\begin{aligned} TFEE_{it} &= \mu_i + \omega X_{it} + \omega_1 \ln ET_{it} \times I\left(\ln pGDP_{it} \le \gamma_1\right) \\ &+ \omega_2 \ln ET_{it} \times I\left(\gamma_1 < \ln pGDP_{it} \le \gamma_2\right) + \omega_3 \ln ET_{it} \\ &\times I\left(\ln pGDP_{it} > \gamma_2\right) + \varepsilon_{it} \end{aligned} \tag{6}$$

Variable description

The explained variable: total factor ecological efficiency (*TFEE*) In this paper, the super-efficiency slack-based measure model (SBM) considering non-expected outputs was adopted to evaluate total factor ecological efficiency, effectively avoiding efficiency overestimation and non-radial adjustment of input and output efficiency. When conditions are relaxed, it is more realistic to assume that returns to scale are variable. Simultaneously, a non-directed SBM was selected, and the adjacent reference Malmquist index (adjacent Malmquist) was measured using Max DEA Pro software. For choosing input and output indicators, following Yan et al. (2020) and Shen et al. (2020), we creatively added ecological footprint measured using improved energy ecological method (Yang and Zhu 2016; Tan and He 2016). Table 1 presents the inputs of various biological and energy accounts.

Core explanatory variable: energy technology innovation (***l nET***) We divided energy technology innovation into two categories: the advancement of fossil fuel technology and research on the exploitation and application of clean energy technologies (Sagar 2002). In China, clean energy technology innovation is primarily manifested in the technological innovation of non-fossil energy (such as the energy of wind, ocean, and biomass energy). Technological innovation in the original energy system is mainly reflected in the improvement and breakthrough of technologies, such

Table 1 The index list

Input	Capital
	Labour
	Ecological footprint
Output	Gross domestic product
	Carbon dioxide emissions

as energy conservation and pollution reduction (Guo et al. 2013). Accordingly, we comprehensively defined energy technology transformation from two perspectives of technology innovation in new energy utilisation as well as energy conservation and emission discharge. Drawing on the practices of Ye et al. (2018), Fan and Sun (2020), and Li and Lin (2016), patent applications for 'clean energy' and the number of patent applications for 'emission reduction and energy conservation' represent the two aspects of energy technology innovation described above.

Threshold variable: economic growth (ln ***pGDP***) Drawing lessons from existing research, we used the deflated regional real per capita GDP to evaluate the threshold variable of economic growth level after it is processed logarithmically.

Control variables: capital affluence (CAP) Capital affluence (CAP) is represented by the ratio of the industrial sector's equity to GDP. Population density ($P\ OP$) is represented by the number of permanent residents per unit area at year end (Qiu and Zhou 2020). Environmental regulation (REG) is indicated by the proportion of completed pollution control in GDP (Wang and Zhang 2016). Degree of openness is indicated through FDI. Because foreign direct investment can affect the environment and regional economy through technology or knowledge spillovers and pollution transfer effects (Ma and Zhang 2014), the degree of openness is calculated by dividing foreign direct investment by gross domestic product.

Spatial weight matrix: 0–1 adjacent distance weight matrix Based on Rook's neighbours, we established a 0–1 adjacency matrix. In particular, when two spatial decision-making units have a common boundary, it is 1; otherwise, it is 0. Furthermore, we used Stata15.0 software to conduct row standardisation on the weight matrix: that is, the sum of elements in each row is 1. Accordingly, the Moran index is between − 1 and 1, and the value of each element in the column vector obtained by $W * X_{it}$ indicates the average value of all its neighbouring regions. The significance of 0–1 spatial weight matrix lies in that the spatial correlations can occur only when two regions are adjacent. In the matrix construction, it is assumed that Hainan Province and Guangdong Province have the condition of being adjacent to Rook. The following is the spatial weight matrix established in this paper.

$$\omega_{ij} = \begin{cases} 1, \text{ region } i \text{ and region } j \text{ are adjacent} \\ 0, \text{ region } i \text{ and region } j \text{ are not adjacent} \end{cases} \tag{7}$$

Data source

We selected 30 mainland regions in China as the research data and considered 2000 to 2017 as the research period. We have eliminated the detailed data on Hong Kong, Taiwan, Tibet, and Macao due to missing information. The data on total factor ecological efficiency were obtained from *China Statistical Yearbook* and *Wind—Economic Database*. The data on energy technology innovation were acquired from the public patent database retrieved by *Shanghai Intellectual Property (Patent) Public Service Platform.* The search scope was 'non-fossil energy' and 'energy conservation and emission reduction' technologies in the specific operation. The abstract and keywords were 'solar energy *or* wind energy *or* ocean energy *or* biomass energy *or* nuclear energy *or* hydrogen energy *or* hydro energy *or* geothermal energy *or* chemical energy *or* renewable energy *or* new energy' and 'energy-saving and pollution reduction', respectively. Simultaneously, specific types of patents were set as invention patents and utility model patents after excluding design patents. The data on the consumption of various types of energy were mainly acquired from the *China Energy Statistical Yearbook*, *National Energy Model Integration Platform of Beijing Institute of Technology*, and public statistical information. The data on economic development level and control variables were obtained from *China Statistical Yearboo*k, *China Population and Employment Statistical Yearboo*k, and *Annual Database by Provinces* on the website of the *National Bureau of Statistics.*

We set the base period as 2000, deflated the prices of all monetary quantities, and adjusted them to comparable prices through a basket of price indexes such as fixed asset investment price indexes to avoid the lack of credibility and comparability of the data caused by price fluctuations. Moreover, logarithm processing was performed on the relevant indicators for fear of heteroscedasticity and multicollinearity. The specific descriptive statistical results of the correlation coefficient matrix of each variable are presented in Table 2.

Empirical analysis of the effect of energy technology innovation on TFEE

Estimation result of the spatial econometric model

Spatial correlation test

We first analysed the spatial correlation of economic activities before proceeding with the specific selection and

Table 2 The descriptive statistics of variables

Variable	Average	Variance	Max	Min
TFEE	0.999	0.174	1.651	0.455
lnET	5.188	1.611	8.959	0.000
CAP	0.542	0.153	1.305	0.243
POP	0.043	0.061	0.383	0.001
REG	0.002	0.001	0.010	0.000
FDI	0.430	0.526	5.480	0.000
lnpGDP	10.021	0.833	11.768	7.881

application of the spatial econometric model. Usually, the Moran index; Lagrange multiplier form (LM-lag, LM-error); and robust form (robust LM-lag, and robust LM-error) tests are adopted one by one. In this study, we first used Moran's index to assess the existence of spatial dependence of the target data. Thereafter, Lagrange multiplier form and spatial effect decomposition were applied to make a more comprehensive judgment. Specifically, the Moran index can be expressed by the following equation:

$$Moran'sI = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} . \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(t_i - \bar{t})(t_j - \bar{t})}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \quad (8)$$

Second, we introduced the Moran scatter diagram and Lisa cluster diagram, the local spatial correlation test indices, to make up for the shortcomings of the global Moran index measurement. Furthermore, we used these diagrams to concretely analyse the spatial distribution characteristics in 30 provinces. The following is the definition of the local Moran index (Moran 1950).

$$Local\ Moran'sI = \frac{n^2}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} . \frac{(t_i - \bar{t})\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(t_j - \bar{t})}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \quad (9)$$

Tables 3 and 4 display that both the provincial total factor ecological efficiency and energy technology innovation in China present an obvious spatial correlation. In recent years, the positive spatial correlation is more pronounced. Meantime, the variation trend of the Moran index in different years was inconsistent, indicating that the inter-provincial total factor ecological efficiency and energy technology transition are considerably affected by spatial distribution in China, thereby presenting a prominent spatial cluster feature. Figure 1 expresses the partial Moran scatter plots of the mean total factor ecological efficiency, and Fig. 2 presents the partial Moran scatter plots of the mean energy technology innovation during the sample period. The first and third quadrants cover most of the points. This figure illustrates that both indicators exhibit the feature of 'high–high' aggregation (Beijing, Tianjin, Shanghai, and other provinces) and

Table 3 Spatial correlation test of *TFEE*

Year	*TFEE*	
	Moran	*Z*-score
2000–2001	0.451***	3.934
2001–2002	0.280***	2.533
2002–2003	−0.043	−0.066
2003–2004	0.028	0.507
2004–2005	−0.062	−0.232
2005–2006	−0.090	−0.489
2006–2007	0.279***	2.637
2007–2008	−0.038	−0.031
2008–2009	0.074	0.894
2009–2010	0.166**	1.653
2010–2011	0.187**	1.886
2011–2012	0.238***	2.323
2012–2013	0.204**	2.030
2013–2014	0.185**	2.001
2014–2015	0.148**	1.661
2015–2016	0.169**	1.962
2016–2017	0.071	0.970

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

'low–low' aggregation (Qinghai, Xinjiang, Yunnan, and other mid-west regions), suggesting an internal efficiency level with strong spatial similarity.

The Moran index test is a preliminary test of spatial dependence and heterogeneity of total factor ecological efficiency. Before a formal analysis of spatial measurement models, we should estimate the non-spatial panel models and examine their statistics; that is, the existence of spatial correlation should be further judged using the LM test. In this paper, we combined four types of models for model estimation, such as the OLS and the time fixed-effect models (Xiao et al. 2018). Table 5 summarises the results for several types of models. The LM and robust LM tests of the four panel models indicated a significant bias in the traditional panel model, which is non-spatial. Instead, it remains essential to establish the spatial econometric model.

We adopted the universally recognised test rules, Lagrange multiplier, Wald, and LR tests to select specific types of spatial econometric models (SDM, SLM, and SEM) (Su and Yu 2020). The detailed steps are as follows: (1) first, we determined the statistical significance level of LM-lag and LM-error. If only the former was significant, SLM was selected. If only the latter was significant, SEM was selected. If both were significant, the robust LM test had to be further judged, with the same test rules as the LM test. When both were significant, the model with extensive statistics was selected. (2) Second, we determined whether the SDM model can be degraded into SLM or SEM through

Table 4 Spatial correlation test of *lnET*

Year	*lnET*	
	Moran	*Z*-score
2000	0.000	0.287
2001	0.081	0.950
2002	0.097	1.084
2003	0.028	0.530
2004	0.078	0.934
2005	0.052	0.718
2006	0.115	1.232
2007	0.160*	1.586
2008	0.168**	1.653
2009	0.198**	1.903
2010	0.217**	2.051
2011	0.293***	2.687
2012	0.266***	2.437
2013	0.217**	2.049
2014	0.253***	2.355
2015	0.293***	2.644
2016	0.270***	2.463
2017	0.213**	2.009

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

Wald and LR tests. Wald test assesses whether SDM can be degraded into SLM, and LR test assesses whether SDM can be degraded into SEM. Notably, only when the Wald and LR test results are consistent with LM test results, SDM can degenerate into SLM or SEM. Otherwise, the SDM model should be established.

According to the LM test judgment rule and statistical test in Table 5, we focused on the results of the SLM.

Empirical results of the spatial Durbin model

The indispensable test in selecting the spatial econometric model was the SDM degradation test, namely the Wald and the LR tests. As indicated in Table 6, the *P* values of the two kinds of tests were less than 0.01, implying that SDM could not degenerate into other models. At this moment, the spatial Durbin model was used. For selecting specific effects, models of specific effects were considered through the Hausman and LR tests. In line with Table 6, the three test statistics passed the 1% significance level, indicating an invalid original hypothesis. Therefore, we finally chose to establish the dual fixed-effect spatial Durbin model.

Table 7 presents that the coefficients ρ of the spatial lag term were significantly positive, further confirming the positive spatial correlation of the regional total factor ecological efficiency. With regard to the internal regions, the effect of energy technology patent (*lnET*) on total factor

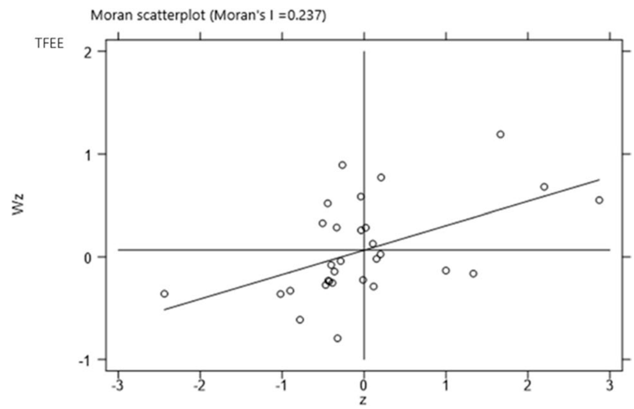


Fig. 1 The local Moran index of average *TFEE*

ecological efficiency (*TFEE*) presented a U-shaped pattern, thereby indicating a change from negative to positive. Capital affluence (*CAP*) exerted an effectively positive force on total factor ecological efficiency. Population density (*POP*) adversely affected total factor ecological efficiency to some extent. From a spatial perspective, by integrating $Wx * lnET$ and $Wx * (lnET)^2$, we observed an apparent spatial effect between energy technology innovation patents and regional green development, which displayed a U-shaped change. Notably, the spatial lag coefficient of energy technology innovation $Wx * lnET$ and its square term $Wx * (lnET)^2$ was − 0.276 and 0.021, and the regression coefficient of energy technology innovation and its square term without spatial factor ($lnET$ 、ln^2ET) was − 0.054 and 0.006. The spatial effect of energy technology innovation on total factor ecological efficiency was much more significant, which cannot be ignored. In terms of the four control variables, except for the level of environmental regulation *Reg*, other variables demonstrated significant spatial influence.

One of the main characteristics of the spatial Durbin econometric regression is the spatial rebound effect between

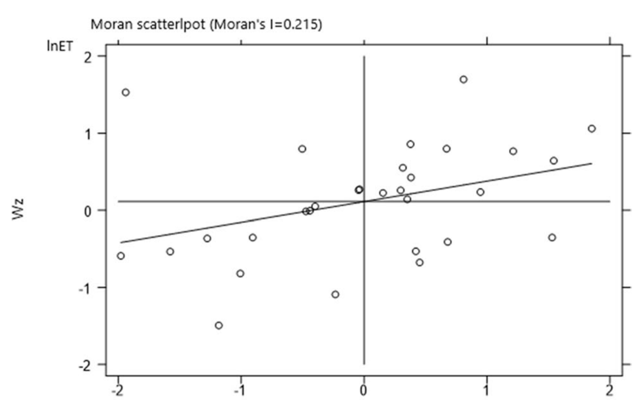


Fig. 2 The local Moran index of average *lnET*

Table 5 Non-spatial panel LM test

Panel type	Mixed OLS	Spatial fixed	Time fixed	Spatial and time fixed
LM-lag	99.258***	296.083***	32.278***	0.492
Robust LM-lag	11.930***	59.900***	19.512***	3.655*
LM-error	155.699***	255.923***	16.179***	0.035
Robust LM-error	68.371***	19.739***	3.413*	3.198*
Log L	434.124	563.810	559.029	885.218

LM and robust LM refer to Lagrange multiplier test and robust test, respectively

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

Table 6 SDM degradation test results

Test	Statistics	*P* value
Wald-SLM	77.210	0.000
Wald-SEM	83.190	0.000
LR-SLM	73.150	0.000
LR-SEM	76.970	0.000
Hausman	373.520	0.000
LR-ind	141.650	0.000
LR-time	208.080	0.000

variables (Xiao et al. 2018). Hence, solely relying on the effects of variables and their lagged items could not fully reflect their spatial correlation. More critically, we focused on the spatial decomposition effects after treating the spatial econometric model with partial differentiation, including spatial direct, spatial spillover, and the total spatial effects. Figure 3 displays the primary route of spatial effects. The spatial direct effect is expressed as the influence of the core variable x_{it} on the explained variable y_{it} within the region. The direct space effect includes direct influence and indirect influence. Direct influence is manifested as the internal influence of x_{it} on y_{it}, and indirect influence is known as feedback influence—x_{it} first acts on the explained variable y_{jt} in the external area through spatial spillover; then, y_{jt} further produces a feedback effect on y_{it} based on spatial correlation (Yuan et al. 2020). The spatial indirect effect, regarded as the spatial spillover effect, is the average spillover influence of the core variable x_{it} on y_{jt} of external regions. The total effect is a comprehensive overview of direct spatial effect and spatial indirect effect, including the influence of x_{it} on y_{it} and y_{jt}, namely, the sum of spillover influence, feedback influence, and internal effect (Su and Yu 2020).

Table 8 demonstrates the spatial effect decomposition results for short term and dynamic long term. The following is the concrete analysis. (1) In the direct spatial effect, a nonlinear U-shaped relation existed between regional technological innovation and provincial total factor ecological efficiency. This result implies that the number of energy technology patents differently affected green productivity in various areas. In view of the coefficient, every 1% change in the weighted number of the energy technology innovation in the early stage reduced the regional total factor ecological efficiency by 0.073% and increased the economic level by 0.006% in the later stage. Meanwhile, compared with the short-term direct effect, the significance level of the long-term direct effect had no noticeable change; however, the influence coefficient was more considerable, manifesting a substantial long-term effect.

Table 7 Parameter estimation of SDM model

Effect type	Spatial fixed		Time fixed		Spatial and time fixed	
Variable	Coefficients	*Z* values	Coefficients	*Z* values	Coefficients	*Z* values
lnET	0.029	1.430	0.066***	4.060	−0.054***	−2.620
(lnET)²	0.001	−0.210	−0.002	−1.350	0.006***	3.390
CAP	0.242***	3.860	0.176***	4.140	0.262***	4.380
POP	−0.802	−1.370	−0.373***	−3.060	−2.042***	−3.580
REG	3.784	0.790	−19.088***	−4.610	3.468	0.730
FDI	0.002	0.140	−0.009	−0.660	0.007	0.520
*W*lnET*	−0.055*	−1.840	−0.019	−0.670	−0.276***	−6.910
W(lnET)²*	0.007***	2.890	0.004*	1.680	0.021***	7.350
*W*CAP*	−0.303***	−2.660	−0.004	−0.050	−0.194*	−1.720
*W*POP*	−6.176***	−4.120	−0.773**	−2.290	−9.064***	−6.330
*W*REG*	19.446**	2.200	−6.463	−0.590	−5.624	−0.510
*W*FDI*	−0.026	−0.630	−0.005	−0.130	0.077*	1.820
ρ	0.625***	17.530	0.289***	4.970	0.188***	3.130
σ^2	0.010***	15.890	0.012***	16.250	0.008***	16.35
Log-likelihood	451.805		418.592		522.631	

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

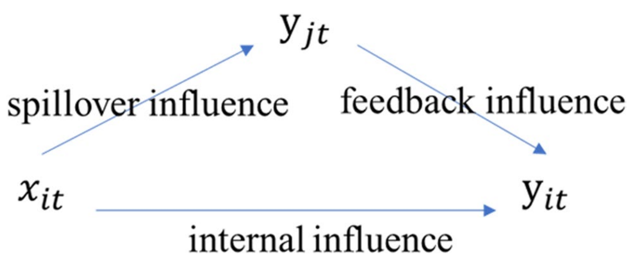


Fig. 3 Schematic diagram of spatial effect decomposition

Table 8 The decomposition of spatial effect

Effect type	Variable	Short-term SDM		Long-term SDM	
Direct effect	*lnET*	−0.073***	−3.420	−0.080***	−3.700
	(lnET)^2	0.006***	3.400	0.007***	3.650
	CAP	0.248***	4.170	0.245***	4.070
	POP	−2.973***	−4.730	−3.210***	−5.050
	REG	3.199	0.630	2.997	0.580
	FDI	0.015	1.020	0.017	1.130
Indirect effect	*lnET*	−0.355***	−6.980	−0.392***	−6.860
	(lnET)^2	0.027***	7.470	0.030***	7.280
	CAP	−0.226	−1.630	−0.221	−1.460
	POP	−11.953***	−6.400	−13.237***	−6.330
	REG	−11.504	−0.790	−12.158	−0.770
	FDI	0.096*	1.860	0.106*	1.870
Total effect	*lnET*	−0.429***	−7.490	−0.472***	−7.300
	(lnET)^2	0.033***	7.630	0.036***	7.430
	CAP	0.022	0.140	0.024	0.140
	POP	−14.927***	−7.430	−16.447***	−7.210
	REG	−8.305	−0.500	−9.160	−0.500
	FDI	0.111**	1.990	0.123**	1.990

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

(2) In terms of spatial spillover effect, the overflow effect of energy technology on ecological efficiency in external regions indicated a U-shaped relation, consistent with the analysis results and providing empirical support for Hypothesis 1. The long-term impact coefficients of energy technology innovation and its square term were −0.392 and 0.030; in the short term, the elastic coefficients of energy technology innovation and its square term were relatively small, which were −0.355 and 0.027, respectively. This result indicates that in the long run, the spatial effects would be greater than the short-term spillover effects. In addition, the inter-regional impact coefficients of energy technology innovation were all greater than its direct effect coefficients, indicating that the spatial indirect effect of energy technical patents cannot be ignored. (3) In terms of the total effect, as energy technology innovation equally affects total factor ecological efficiency with regard to the direct and indirect influence, its cumulative total effect was more prominent with a more significant level. Similarly, the total spatial effect indicated a significant U-shaped effect, verifying the first half of Hypothesis 2. In general, an apparent U-shaped influence existed between energy technology innovation and regional total factor ecological efficiency. Furthermore, the spatial spillover effect of energy technology innovation was much stronger and emerged as a stable long-term shock.

Robustness test

In the spatial panel, the validity and applicability of the parameter estimation were closely related to the choice of the spatial matrix. The results may differ significantly depending on the type of matrix. Consequently, we chose two spatial weight matrices concerning the geographic distance and information distance as a robustness test of the model to provide evidence for the credibility and stability of the above empirical results of the spatial Durbin model and its decomposition effects. Table 9 presents the models of two types of robustness tests conducted on the basis of double-fixed SDM models. The results revealed that the number of significant variables and the influence direction of the variable coefficient were the same as the results in this paper. Moreover, no contradiction existed between the three types of effects and the above conclusions, and the spatial effect coefficient was more prominent, manifesting a rational model establishment.

Estimation result of the threshold panel model

Empirical results of the threshold panel model

Theoretical and statistical analyses indicated that the core for the complex connection between energy technology innovation and total factor ecological efficiency lies in the intervention of intermediate mechanism. In light of the highly uneven development of various provinces in China, this study empirically explored the complex mechanism between energy technology innovation and regional total factor ecological efficiency under the heterogeneous level of economic growth in different areas. In the threshold model, the value of *F* statistic and the corresponding self-sampling *P* value were obtained after 400 repeated sampling, as demonstrated in Table 10. According to the significance level in Table 10, we determined that the model not only passed a single threshold but also had a second threshold. In other words, a double threshold effect of economic development level is highly possible, with two thresholds at 9.0933 and 9.5651. We analysed the double threshold effect in detail.

We further identified the threshold value by the feat of the least square likelihood ratio statistic LR to acquire the threshold and the confidence interval more intuitively. The

Table 9 SDM robustness test

Matrix type		The geographical distance weight matrix		Information distance weight matrix	
Effect	Variable	Coef	z	Coef	z
Main	*lnET*	−0.065***	−3.100	−0.079***	−3.810
	(lnET)^2	0.005***	2.940	0.007***	3.710
Wx	*W*lnET*	−0.624***	−5.010	−1.242***	−5.890
	W(lnET)*^{2}	0.066***	6.590	0.100***	6.680
Direct	*lnET*	−0.050**	−2.270	−0.063***	−2.940
	(lnET)^2	0.004*	1.920	0.005***	2.920
Indirect	*lnET*	−0.384***	−4.060	−0.966***	−4.390
	(lnET)^2	0.041***	5.280	0.078***	4.600
Total	*lnET*	−0.433***	−4.640	−1.030***	−4.630
	(lnET)^2	0.045***	5.800	0.083***	4.830
Log-likelihood		504.361		505.932	

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

Table 10 The statistics of different threshold effects

Threshold	F value	P value	Critical value		
			1%	5%	10%
Single	127.250***	0.000	32.344	41.592	47.621
Double	33.450***	0.000	17.957	20.991	22.938
Triple	11.630	0.880	37.319	38.668	55.505

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

threshold estimate is the statistic when LR is 0. Figure 4 displays the likelihood ratio function graph.

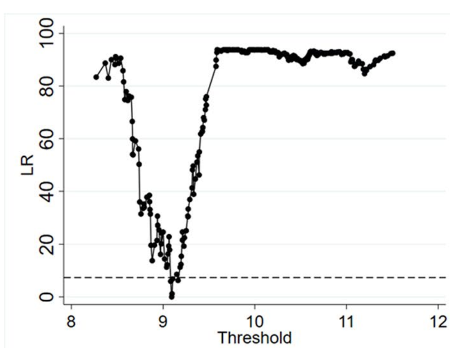
Table 11 presents the two existing thresholds and their confidence intervals of the threshold model, which were obtained through software analysis. As in Fig. 3, the threshold values at the 95% confidence level were [9.0626, 9.1199] and [9.4934, 9.5788], respectively, and all the LR values were less than the critical value of 7.35 at the significance level of 5% (as shown by the dotted line in the figure).

Table 11 Thresholds and confidence intervals

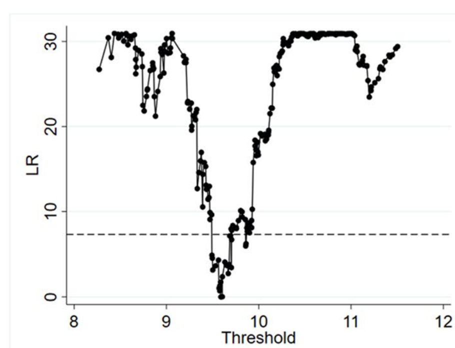
Test	Threshold value	95% confidence interval
Single threshold	9.0933	[9.0626, 9.1199]
Double threshold	9.5651	[9.4934, 9.5788]

Following the threshold regression (as seen in Table 12), the effect of energy technology patents on total factor ecological efficiency was not monotonically incremental (or depressive). The effect coefficient of energy technology innovation varied evidently in different provinces. As the economic growth level increases, it first inhibits the regional total factor ecological efficiency and then has an opposite effect. To a certain extent, it is consistent with the 'U'-shaped curve in the spatial Durbin model with the addition of spatial lag term and direct spatial effect. Specifically, if the level of economic gain is smaller than 9.0933, each 1% optimisation of energy technology innovation will lead to a 0.056% decrease in the level of the green economy. When the value of per capita income crosses the first threshold, that is, when *lnpGDP* is between 9.0933 and 9.5651, the parameter estimate becomes smaller but insignificant. This result reveals that as the economic development of a region continues to rise, its inhibitory effect is weakened and is not significant. Once the adjustment variable is larger than 9.5651, there will be a structural mutation in the relation between the two. The elasticity coefficient of energy technology innovation activities turns to 0.017, which is significant at the level of 5%. Thus, the paper's second theoretical assumption is further validated. The above results illustrate that the optimal interval is the high-value interval of the economic growth level, at which point energy technology

Fig. 4 The function graphs of the likelihood ratio of two threshold values (**a**) and (**b**)



(a)



(b)

Table 12 The estimation results of the double threshold effect model

TFEE	Coef	Std. Err	*t*	*P*>|*t*|	95%	Conf. interval
CAP	0.199***	0.074	2.690	0.007	0.054	0.344
POP	0.397	0.645	0.610	0.539	−0.871	1.665
REG	13.662**	5.531	2.470	0.014	2.795	24.530
FDI	−0.012	0.017	−0.730	0.463	−0.045	0.020
$lnET(lnpGDP \le 9.0933)$	−0.056***	0.012	−4.630	0.000	−0.080	−0.033
$l\ nET\ (9.0933 < lnpGDP \le 9.5651)$	−0.010	0.010	−0.960	0.336	−0.031	0.011
$lnET\ (lnpGDP > 9.5651)$	0.017**	0.008	2.200	0.028	0.002	0.031
cons	0.827***	0.054	15.330	0.000	0.721	0.933

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

Table 13 Robustness test of the threshold model

Model	Model (1)		Model (2)	
TFEE	Coef	*t*	Coef	*t*
CAP	0.188**	2.570	0.174**	2.390
POP	0.342	0.540	0.206	0.330
REG	14.988***	2.730	13.518**	2.430
FDI	−0.015	−0.930	−0.006	−0.380
$lnET\ 1\ (lnpGDP \le 9.0982)$	−0.053***	−4.380		
$lnET1\ (9.0982 < lnpGDP \le 9.5897)$	−0.005	−0.510		
$lnET1\ (lnpGDP > 9.5897)$	0.018**	2.350		
$lnET\ 2\ (lnpGDP \le 9.0934)$			−0.077***	−6.390
$lnET2\ (9.0934 < lnpGDP \le 9.6052)$			−0.009	−0.970
$lnET2\ (lnpGDP > 9.6052)$			0.018***	3.010
cons	0.826***	15.100	0.847***	16.240

The statistical values at 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively

innovation can raise regional total factor ecological efficiency in a more productive way.

Robustness test

A robustness test was inevitably performed to examine the threshold effect of different types of energy technology innovation on total factor ecological efficiency to avoid instability of the estimation. Therefore, energy technology innovation was divided into technology innovation for energy conservation and emission reduction of traditional energy *lnET 1* and technology innovation for comprehensive utilisation of renewable energy *lnET 2*. We conducted threshold regression for the two mentioned variables, and the estimation is summarised in Table 13. For each type of energy technology innovation, no significant fluctuations occurred in the value of the impact coefficient or the level of significance. More specifically, both the threshold effect and threshold value were similar to the above, and no apparent fluctuation was observed in the measurement results of the control variables. On this basis, the threshold model constructed in this paper had good robustness.

Discussion

Spatial econometric results revealed that provincial total factor ecological efficiency in China presents strong spatial agglomeration characteristics, consistent with the research findings of scholars such as Shen et al. (2021) and Li et al. (2021a, b). However, different from existing studies, the spatial effect of technological innovation is not constant when energy technology factors are considered (Li et al. 2021a, b), a notable finding. The spatial Durbin model indicates a significant U-shaped spatial influence between energy technology innovation and total factor ecological efficiency, among which the spillover effect between regions is larger. The reason may lie in that although energy technology patent is a type of intangible asset, the positive externality of technical and intellectual achievements facilitates the circulation and imitation of technology elements (Marshall 1890; Romer 1986). In the short term, the increase in energy technology stock within a region widens the technology stock gap between neighbouring regions, limiting the spatial diffusion and absorption of technological innovation (Caniëls 2000). Meanwhile, the attraction of green technology-developed regions to crucial elements of surrounding regions dramatically reduces the efficiency of resource allocation, which is not conducive to the improvement of total factor ecological efficiency of external regions (Luo et al. 2020). By contrast, in the long run, the coordinated improvement of regional energy technology stock could narrow the regional technology gap and enhance the technology absorption capacity of each region. The diffusion of energy technology between regions will make up for the disadvantages of factors driven by profit, upgrade the industrial structure and improve productivity, and accelerate the development of green economy in external regions (Hirschman 1958; Zhou and Peng 2019).

In accordance with the double threshold effects, a U-shaped relation exists between energy technology innovation and regional total factor ecological efficiency, which provides sufficient evidence for the complex non-linear relation among the three. Scholars represented by Du and Li (2019) argued that energy innovations only promote total factor efficiency in economies with high income. Slightly different from that, we observed that energy technology innovation can also play a significant role in regions with low economic growth. The probable reason may be that affected by social and economic systems, low-income areas focus more on the improvement of economic aggregate rather than on the pursuit of green development goals (Popp 2012). Such regions do not possess hardware facilities for energy technologies and soft environment support for investment and financing (Wang et al. 2021a, b), leading to resource occupation and capital crowding out effect and thereby adversely affecting total factor ecological efficiency. As the regional economic growth reaches a certain level, CO2 emissions show a downward trend, and an intensive development model is gradually formed (Fan and Sun 2020). Under the impetus of energy technology innovation, economic and environmental benefits should be considered. Moreover, a better economic foundation can ensure a sound infrastructure supply and stable market conditions, enabling the adoption of energy technologies across the 'Valley of Death' (COMMITTEE ON SCIENCE, U.S. HOUSE OF REPRESENTATIVES 1999). Thus, these measures will help obtain the utmost out of the environmental protection advantages of carbon-free energy technology innovation and effectively promote regional ecological efficiency.

Conclusions and suggestions

Considering the STIRPAT model framework in environmental economics, this paper discusses the complicated effects of energy technology innovation on provincial total factor ecological efficiency in China. Based on the sample data of 30 regions in China from 2000 to 2017, this paper first adopts a requisite spatial correlation test and the spatial Durbin model based on three types of spatial weight matrices to probe the dynamic spatial association between energy technology innovation and green economic development. As far as the spatial effect is concerned, we conduct a careful analysis of the spatial spillover effect of technology and successfully verify Hypothesis 1 that energy technology innovation does have a remarkable 'U'-shaped spatial spillover effect on regional total factor ecological efficiency. Moreover, the mechanism of the non-linear relation between the two is further studied. Under the regulation of regional economic growth level, this study investigates the sophisticated correlation between energy technology innovation and total factor ecological efficiency during the energy transition period, confirming Hypothesis 2 that with the increase of regional economic growth, the impact of energy technology innovation on regional total factor eco-efficiency presents a trend from negative to positive. In short, our main conclusions are summarised as below: (1) considering the ecological input, the total factor ecological efficiency appears to have a positive spatial influence among provinces in China, presenting the feature of 'high–high' and 'low–low' spatial agglomeration. Energy technology innovation, which covers emission reduction and conservation technologies and development and utilisation technologies of renewable energy, also appears to have apparent spatial dependence characteristics. (2) Energy technology innovation can exert obvious spatial influence on regional total factor ecological efficiency. Regardless of the direct spatial effect, spillover effect, or total effect, all show a U-shaped relation, among which the effect of spatial spillover is more substantial and the long-term effect is more remarkable. (3) The influence of innovation activities in energy technology on regional total factor ecological efficiency is characterised by a non-linear shock with the regional economic growth level as the threshold. As the per capita income level of the region keeps breaking through the inflection point, the influence of energy technology innovation on regional total factor ecological efficiency changes from restraining to promoting. In the provinces with a high level of economic growth, energy technology innovation can prominently increase regional total factor ecological efficiency. In economies with medium growth, energy technology patents have not worked very well.

The improvement of ecological efficiency is not only a symbol of China's green and sustainable development but also a guarantee of China's international commitment to carbon reduction and carbon neutrality. Accelerating energy transition driven by technology innovation is a crucial action to improve regional total factor ecological efficiency. For this purpose, suggestions are given in three aspects. (1) Coordinate the promotion of open innovation of energy technology and realise the regional application of cutting-edge energy technology. While improving the regional energy technology innovation capability, the spatial spillover impact of energy technology on ecological efficiency is fully demonstrated through inter-regional open innovation. By this means, the absorption and transformation of cutting-edge energy technology can be effectively realised to exert more decisive impetus on innovation-driven regional low-carbon green economic development. (2) Collaborate to increase the regional energy technology stock and fully demonstrate the space spillover advantage of energy technology. On the one hand, we should focus on the development of generic energy technologies, carry out trans-regional R&D cooperation on low-carbon development, and form an exchange mechanism for new processes and technologies to maximise the spillover impact of energy technology innovation. On the other hand, it is feasible to shape the mode of cooperation among enterprises, universities, and research institutes, which can further help realise the trans-regional transformation of energy technology achievements and improve the social and economic benefits of energy technology application. (3) Adopt dynamic, differentiated, and targeted measures for green development based on regional economic growth level. Furthermore, follow the principle of applying proper therapeutic measures in line with local conditions and individuality to formulate regional development. In areas with weak economies, such as some western provinces in China, accelerating the development of economic intensiveness and focusing on the introduction and creation of energy technologies are essential to give full play to the latecomer advantages of energy technology innovation in green development and change the existing disadvantaged situations. In economies with high growth level, such as eastern China, creating a suitable environment for energy technology innovation, increasing investment in related fields, and fostering a sense of crisis of green development and market competition for enterprises are essential to improve the efficiency and scale of energy technology innovation in 'bellwether' regions.

Appendix

Table **14**
Table **15**

Table 14 Ecological footprint account

Land type	Species of biological resources
Arable land	Cereals, beans, potatoes, cotton, oil plants
Woodland	Wood, tea, fruit, apple, pear, grape
Grassland	Beef, pork, mutton, milk, poultry eggs
Fossil energy land	Crude oil, natural gas, kerosene, coke, diesel, gasoline, fuel oil, coal
Construction land	Electric power
Water area	Fish, shrimp, crabs, and other aquatic products

Table 15 The region division of different threshold interval

Year	Low level of economic development	Intermediate level of economic development	High level of economic development
2000	Other provinces except Shanghai	Shanghai	
2004	Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	Tianjin, Zhejiang	Beijing, Shanghai
2008	Shanxi, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang	Hebei, Inner Mongolia, Liaoning, Jilin, Fujian, Shandong	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong
2012	Guizhou, Gansu	Shanxi, Heilongjiang, Anhui, Jiangxi, Henan, Hunan, Guangxi, Hainan, Sichuan, Yunnan, Qinghai, Ningxia, Xinjiang	Beijing, Tianjin, Hebei, Inner Mongolia, Liaoning, Jilin, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Hubei, Guangdong, Chongqing, Shaanxi
2017		Yunnan, Gansu	Other provinces except for Yunnan and Gansu

Abbreviations DEA: Data envelopment analysis; SFA: Stochastic frontier analysis; SDGs: Sustainable Development Goals; STIRPAT: Stochastic Impacts by Regression on Population, Affluence, and Technology; SDM: Spatial Durbin model; SLM: Spatial lag model; SEM: Spatial error model; SBM: Slack-based model; TFEE: Total factor ecological efficiency; ET: Energy technology innovation; CAP: Capital affluence; POP: Population density; REG: Environmental regulation; FDI: Degree of openness; R&D: Research and Development; VAR: Vector autoregression

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Declarations

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