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How does energy technology innovation affect total factor ecological efficiency: Evidence from China

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Abstract: Recently, with the dual constraints of resources and environment, to accelerate the transformation of low-carbon energy driven by energy technology innovation has become a global development trend. On account of the provincial data during the period of 2000 to 2017, we creatively incorporate the ecological footprint into the measurement of total factor ecological efficiency so as to infer the coordinated development level of 3E system more precisely. In this paper, the dynamic spatial impact of energy technological innovation on regional total factor eco-efficiency is explored through the spatial Durbin model, and the complex nonlinear relationship between the two is further probed by constructing the panel threshold model. The following conclusions are obtained ultimately. First of all, both China's provincial ecological efficiency and energy technology innovation activities possess significant spatial positive correlation, which manifests as the spatial geographical distribution agglomerated by the similar characteristics; Secondly, the regional energy technology innovation has a remarkable spatial effect on ecological efficiency, which displays a U-shaped trend. And compared with the direct effect, the spatial spillover effect is more intense, along with more stronger long-term influence; Finally, taking the level of regional economic development as the moderating variable, the impact of energy technology innovation on eco-efficiency emerges a conspicuous threshold effect with two threshold values. Only when the level of economic development crosses the double threshold, can energy technology innovation activities significantly improve the regional total factor ecological efficiency. After the robustness test and discussion of the empirical model, relevant policy suggestions are put forward based on the conclusions of the paper.

Key words: Energy technology innovation; Total factor ecological efficiency; Ecological footprint; Spatial Durbin model; Panel threshold model

1. Introduction

The deterioration of the ecological environment brought by the massive mining and utilization of fossil fuels, as well as the pollution emissions caused by energy consumption, have increasingly exceeded the environmental carrying capacity, thus posing a potential threat to both the economic security and social stability (Xu et al. 2019). Nevertheless, the problems of environmental protection and resource security are bound to affect the sustainable development of human society. The United Nations Climate Change Conference, which has a history of 25 years so far, has gone through four important stages: the Convention, the Kyoto Protocol, the Bali Road Map and the Durban Platform. Against the backdrop of global climate change and environmental degradation, the world has substantially entered the stage of low-carbon development (Chen and Golley 2014; Deng and Yang 2019). With the promotion of clean energy revolution, energy transformation is stepping into a historical climax in the world. To be specific, the basic path of the energy transition can be attributed to two aspects of energy structure adjustment and energy technology progress (Zhou 2010; Shafiei 2014). In the course of energy transition, compared with the ultimate goal of energy structure transformation, energy technology innovation, as the main driving force of energy transformation, plays a more decisive role in realizing energy system transformation and achieving sustainable development (Wu 2017).

According to China's Action Plan on Energy Technology Revolution and Innovation (2016-2030), a sound energy technology innovation system suited to China's national conditions will be established by 2030, with the overall energy technology level reaching the international advanced level. This is not only a crucial approach to support the synergetic

development of the energy industry and ecosystem in China, but also an ambitious goal of China's becoming a world power in energy technology. At the 75th session of the United Nations General Assembly in September 2020, Chinese President Xi stressed increasing China's outstanding contribution and adopting more forceful policy measures to peak carbon dioxide emissions by 2030 and strive to be carbon neutral by 2060. An innovation-driven systemic transformation of energy is a pivotal prop for achieving China's goal of "carbon neutrality" by 2060, high-quality energy development, and "green recovery" in the post-epidemic period (An 2020). The energy technology has been highly valued in China. In 2015, the Chinese Academy of Engineering launched the "Strategic Research on China's Energy Technology Revolution System" major consulting project, covering nine major projects including nuclear energy, accumulation energy, solar energy, wind power, oil and gas, coal, hydropower, biomass energy, smart grid and energy network integration. In this project, the energy technology route is divided into three phases: forward-looking technologies (2020), innovative technologies (2030) and disruptive technologies (2050) (Zhou 2020).

The construction of ecological civilization is one of the most crucial fundamental strategies of China. The reason why ecological efficiency is widely valued is that it is usually accompanied by lower energy consumption and higher resource allocation rate. In the meantime, a high ecological efficiency is a symbol of a pleasant ecological environment and high-quality economic development. It is worth noting that energy technology innovation activities are inseparable from the coordinated development of economy, ecology and energy. Whereas, this further triggers us to think deeply: How do energy technology innovation activities concretely affect ecological efficiency? How is the result of its impact like? Take it

further, does this influence differ due to the heterogeneity of regional development? In order to explore these issues, this paper discreetly adopts both the spatial Durbin model and threshold panel model to lucubrate detailed influence forms, effects and mechanisms of energy technology innovation on China's regional total factor ecological efficiency, taking China's provincial data from 2000 to 2017 as samples.

Based on this, we may have the following four marginal contributions:①In terms of the definition of energy technology innovation, this paper not only includes the exploitation and application of renewable energy in previous studies, but also brings the targeted energy saving and emission control of traditional fossil fuels into the research framework of energy technology innovation. The comprehensive definition adapts to the current status of China in the energy transition stage better as well as provides profound reference for other developing countries in the period of energy transition; ②The original energy input is substituted by the regional ecological footprint which is measured by advanced energy-ecological footprint method. Since then, the measurement of total factor ecological efficiency has covered multi-dimensional factors such as labor, capital, ecology, energy, pollution output and economic output, which reflects the evolution and current situation of the coordinated development of regional ecological economy across the board; ③ After passing the spatial statistical test of the ordinary mixed panel, this study steps to establish the spatial econometric model and discuss the spatial effects of energy technology innovation on ecological efficiency during the dynamic period, which could partly corrects the possible deviation of previous non-spatial panel models; ④ According to the static threshold panel results, the complex influence and influence mechanism of energy technology innovation activities on the

development of regional green economy under different economic development levels are further analyzed.

This article contains the following structure: Section 2 sorts the domestic and foreign research status of energy technology innovation, economic growth, environmental performance and total factor ecological efficiency; Section 3 provides the theoretical basis and research hypothesis of this paper, and constructs two kinds of econometric models; An empirical results of two econometric models are presented in Section 4; Then Section 5 performs a brief discussion of the empirical findings and the last part summarizes the main conclusions of the research and some pertinent policy recommendations are finally comes up with.

2. Literature review

2.1 Research on the relationship between energy technology innovation and economic growth

In the relevant foreign studies, by analyzing the spillover effect of renewable energy technology in Italy empirically, Magnani and Vaona (2013) found that the spillover effect of renewable energy technology could actively boost the regional economic increase; Built on the Kuznets Curve Hypothesis, Sun et al. (2020) discussed the long-term influence relationship between China's regional economic growth and renewable energy technology, and believed that renewable energy technology innovation would improve economy growth in the long run; Guo (2007) is one of the earliest scholars in China who sensed the connection between energy technology and economic growth. Through VAR and VECM model which were constructed by using the data of China and India from 1965 to 2004, he studied and compared both the

short-term and long-term impact of economic gain and energy factors incorporated into technology between the two countries. It was found that unlike India, the energy technology innovation goes against China's economic growth in the short term whose fluctuations are relatively large; Similarly, after constructing the dynamic CGE and MCHUGE model, Liu and Hu (2014) also probed into the influence of energy technologies on macroeconomic variables in different stages. They finally concluded that the pulling function of energy technology innovation on the economy is distinct, which is even stronger if the non-agricultural sector is mentioned, embodying the advantage for the adjustment of industrial structure in long-term; According to the Laspeyres decomposition results of China's green transformation of industrial economy, Wu (2017) hold that, in contrast to the energy restructure and the environmental effects of clean energy, the reformation in the energy technology is exactly a fundamental way to improve China's green economic growth; On the side, by means of a transcendental function model contained bias technological progress, Qian (2019) sought the economic growth effect of various types of energy saving technological progress through three-stage least square method (3SLS), obtaining that independent innovation of energy technology could exert the largest economic growth effect.

2.2 Research on the relationship between energy technology innovation and environmental performance

Existing studies on the correlation between the innovation in energy technology and environmental performance mainly focus on two aspects -- carbon dioxide emissions and green economy development.

In view of carbon dioxide emissions, taken the European counties as the sample which

cover the data of energy R&D and carbon footprint, both the linear and nonlinear models were built separately by Altıntas and Kassouri (2020). The results showed that during the period of 1985 to 2016, the technological innovation of energy in European countries curbed carbon footprint reduction effectively; As far as the dynamic panel of energy technology patents and carbon dioxide emissions with the regional data in China was concerned, Wang et al. (2012) dicovered that patents related to fossil energy technologies would not impose an effective effect on CO_2 emissions, while patents on carbon-free energy technologies could remarkably reduce CO_2 emissions, especially in the eastern regions; Homoplastically, when the research object was replaced by the carbon intensity, Cheng and Yao (2021) also reached the conclusion of regional heterogeneity, but they deemed that such inhibitory effect of renewable energy technology innovation could only be realized in the long run.

In view of the green economic development, scholars have basically affirmed the positive impact of energy technology innovation, but there was regional heterogeneity in the influence relationship under different conditions, stages and environments. For instance, by conducting empirical research on the sample data of inland provinces in China through VAR model, Zhang (2019) possessed that energy technology patents are positively correlated with the coordination degree of regional ecological construction, which displays distinctiveness in various regions since that such effect hinged on the composition of technology patents and the consumption of energy; Zhang (2015) believed that the relationship between energy technology innovation and green development is not purely linear through the factor substitution effect, drawing the conclusion that the impact of technological progress on energy consumption based on technological innovation demonstrates an inverted U shape; By establishing the partial linear

norm function model, Yan et al. (2020) investigated the association between technology innovation on sustainable energy and green total factor productivity growth at different income levels, confirming that only if the standard of regional income level exceeded the critical point, can the innovation of renewable energy technology play an expected role in total factor ecological efficiency. Once the income level passed the turning point, the total factor ecological efficiency would follow the same trend as the level of income; Moreover, some scholars also pointed out that in areas with backward economic development, energy technological innovation would inflict a two-way externality, that is, the application and promotion of technological innovation in poor areas would be hindered due to the "free rider" behavior, thus overwhelming its beneficial influence on the green development (Ley et al. 2016).

2.3 Research on total factor ecological efficiency

The ecological efficiency is a symbol of the degree of coordination between economy and ecological environment, which is usually represented by the proportion of the economic benefit of productive events to the environmental ecological impact (Schaltegger and Stum 1990). In comparison to the single factor energy efficiency measured by depletion of resources per unit of gross domestic product, what makes the total factor ecological efficiency unique is that it contains various factors of input and output. Therefore, the total factor ecological efficiency is the optimum selection for systematically and comprehensively estimating the development level of green economy under the demand of sustainable development (Li and Hu 2012). On the strength of different methods, scholars have measured the total factor ecological efficiency and obtained different results, thus concluding the status quo of the energy-environment-economy system and its improvement path (Wang et al. 2017).

In the aspect of the measurement methods of total factor ecological efficiency, stochastic frontier analysis (SFA) and data envelope analysis (DEA) are the star approaches in the field of efficiency measurement. For instance, on the basis of SFA, He et al. (2017) proposed the potential space for regional energy saving and pollution reduction in China after evaluating the environmental efficiency in various regions. Yet, it is worthy of attention that compared with SFA, the undesired output represented by environmental impact can be included in the research system, and the independent impact of efficiency changes and technological progress can be distinguished as well by means of DEA. In previous studies, scholars prevailingly analyzed total factor ecological efficiency from the perspectives of labor, capital and energy resource input (Wang et al. 2016). While in recent years, a handful of scholars have realized the importance of ecological input for sustainable development, replaced simple energy consumption with ecological footprint, thus assessing the status quo of regional ecological efficiency and ecological pressure in China (Shi and Wang 2016). The ecological footprint is the total land area consumed by various resources, characterizing the extent of human consumption of resources and the degree of the waste produced by digestion of human nature (Wackernagel and Rees 1996). In comparison to a single index of energy consumption, ecological footprint can mirror the human's consumption of ecological environment and various resources in a more comprehensive way.

In the aspect of the influencing factors of total factor ecological efficiency, scholars have pointed out a variety of factors from multiple perspectives, such as economic scale (Chen and Golley 2014), industrial green transformation (Han et al. 2020), industrial structure (Lin and Du, 2015), technological progress (Yang et al. 2017), technological innovation (Cai and Zhou 2017)

and so on. Through the empirical analysis of China's provincial and regional data, Chen (2016) and Wu (2018) respectively concluded that technological progress and technological innovation are indispensable forces to improve total factor ecological efficiency and build a sound ecological construction. And similarly, Ghisetti and Quatraro (2017) hold homologous views, believing that green technology innovation and energy technology innovation are the tractive power for regional green economic gain and sustainable development.

The existing research related to the innovation in energy technology and total factor ecological efficiency authentically provide the theoretical basis for this paper. However, there are few researches on the relationship between the two all over the world, and there remains some room for improvement in the previous literature.

First of all, the existing research on energy technology innovation is biased towards theoretical research which lacks sufficient empirical test. Nevertheless, in the existing quantitative studies on energy technology innovation, the innovation based on clean energy technology is usually adopted to represent the power of energy innovation, without considering the innovation activities for improving energy conservation and emission reduction of traditional fossil energy. In other words, there is no comprehensive consideration for the current innovation-driven energy structure transformation.

In the second place, the definition and measurement of the total factor ecological efficiency principally started with the input and output indexes. As far as the indicators of input were concerned, only the factors such as labor, capital and energy were considered, with few scholars including the ecological footprint in the research framework (Xing et al. 2018). What calls for special attention is that in the research on energy technology innovation and green

economic growth, there was no literature that examines the relationship between the two from the perspective of ecological consumption.

Moreover, in terms of model application, some scholars have preliminarily confirmed the regional heterogeneity and difference of the impact of energy technological innovation on total factor ecological efficiency through VAR model, dynamic panel model and other models. It is indeed not difficult to find the lack of conventional nonlinear test analysis based on threshold model in empirical research. Simultaneously, the existing research have primarily affirmed the spatial distribution characteristics of the total factor ecological efficiency (Lin 2017). On the other hand, as a branch of technological elements, energy technological innovation may well have the common spatial spillover effect of technological innovation activities. However, it remains certain space in the research on the spatial effects of energy technology innovation on total factor ecological efficiency.

3. Theoretical analysis and research methods

3.1 Theoretical analysis

As a technology element, energy technology itself is a non-competitive public good. When innovation activities are carried out within the region, "energy technology diffusion" and "energy technology spillover" will occur successively, that is, the unconscious outflow and acceptance of technology. Within the region, through the accumulation of knowledge, high-end human capital and other elements, unique energy technology innovation achievements will be formed, such as enterprise production mode, renewable energy development equipment, energy saving and emission reduction devices. The spillover of energy technologies is reflected in the

accelerated transformation of these innovation achievements through the imitation, learning, investment and consumption of external regions, and thus exerts positive externalities, showing that the social benefits are greater than the benefits of individual enterprises. In addition, energy technology reform will also urge the transformation of the green industrial structure in neighboring areas to a certain extent, forming a model for regional energy technology to lead and drive industrial development.

Nevertheless, in the process of energy technology spillover, it does not necessarily lead to the favorable growth of total factor ecological efficiency in different regions. The effect of such influence depends on many factors (Fu 2009), among which the geographical distance, the absorptive capacity of receiving region and the technological diffusion capacity of sending region are the three elements that do really matter (Shangguan 2016). To be specific, the geographical proximity of different regions makes for technical overflow and knowledge diffusion no matter from the perspective of economic development level, or the perspective of the level of transportation and information technology. The closer the geographical location is, the more conducive it is to transform the hidden technology spillover into the explicit technology spillover; As a key influencing factor, the absorptive capacity of technology undertaking region is an abstract concept integrating many factors such as regional social culture, management policy, industrial structure and development level. The degree of economic growth often implies the extent of the region's ability to absorb spillover technology; The diffusion of regional technology is mediated by the accumulation and circulation of human capital, and it has various diffusion effects on the external regions, thus giving play to different technology spillover effects.

On such a basis, this article comes to formulate Hypothesis 1: There is a spatial spillover effect of energy technology innovation on total factor ecological efficiency, and the spatial effect is uncertain.

According to effect of crowding out and factor substitution, the initial energy technology innovation is mostly characterized by high cost, low return and long product innovation cycle, and such immature energy technology innovation cannot bring into play good economies of scale and environmental benefits (Fan 2020). In addition, the innovation input of industrial enterprises in energy utilization and development will crowd out the original productive investment of enterprises to some extent, and produce the crowding out effect on other types of technological innovation, which leads to the low efficiency in distributing enterprises resources and the destruction of overall economic and environmental benefits. According to the infrastructure lock-in effect and the "valley of death" hypothesis, the application and popularization of energy technology in regions with backward economic development is restricted by many institutions, such as technological system, social system and political system (Geels 2007). Due to the imperfect infrastructure construction of energy supply and consumption, the energy technology is easy to fall into the "chicken and egg" paradox, making it hard to develop on a large scale. In regions with different levels of economic development, their market stability and investment environment are widely divergent. Hence, the promotion of energy technology innovation products will face different prospects and risks, and even the application of some energy technology innovation products will fall into the "valley of death" where the capital chain is broken (Ehlers 1999). In terms of the environmental Kuznets curve hypothesis, Naqv et al. (2020) verified the environmental Kuznets hypothesis (EKC) and the

renewable energy Kuznets curve hypothesis (REKC) for high income groups through 155 European countries. Alola (2020) found that among the four types of economies (high, medium high, medium low, low income), energy technology innovation only played a conspicuously inhibiting role on CO_2 discharge in the countries with high and medium income.

In consideration of previous analysis, this study puts forward Hypothesis 2: There is a complex link between the innovation in energy technology and total factor ecological efficiency. Meanwhile, under the adjustment of the level of regional economic development, the influence of energy technology innovation on total factor ecological efficiency appears as a nonlinear shock.

3.2 Research Methods

3.2.1 Spatial econometric model

Characteristics of technology spillovers is widely accepted by the academic point of view. Therefore, this paper focuses on the transformation of energy technology for space effect of total factor of ecological efficiency. On this basis, space factors in the innovation of energy technology are added in the model. The spatial panel Durbin model is firstly constructed, and the statistical tests are used to determine whether the spatial panel Durbin model can be degenerated into the model of spatial lag model or spatial error, and then the spatial effects of energy technology transformation on the total factor ecological efficiency are further explored. In this paper, the spatial Durbin model (Anselin 1988) is constructed as follows:

$$Y = \rho WY + \alpha l_N + X\beta + WX\theta + \varepsilon \quad (1)$$

Where, Y is the column vector of the explained variable $TFEP$ in different regions of each year. Following the STIRPAT framework which is widely used in environmental

economics, this paper selects energy technology innovation ET as a variable to measure technological level and uses 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 eco-efficiency, environmental regulation Reg and openness to the outside world Fdi are also included in this paper. X is a matrix composed of core variable $lnET$, quadratic item and control variables such as Pop、Cap、Reg、Fdi ; WY、WX respectively represent two different interaction effects in spatial metrology，that is endogenous interaction effect and exogenous interaction effect; ρ is the spatial autoregression coefficient, while γ is the spatial autocorrelation coefficient and ε represents the error term. Additionally, the model also contains two parameter column vectors β and θ to be estimated.

3.2.2 Threshold model

This study adopts the non-dynamic panel threshold regression model proposed by Hansen (Hansen 1999) to examine whether there is a threshold effect between energy technology innovation and total factor eco-efficiency. As an econometric model of nonlinear relation test, this method can not only accurately calculate the threshold value, but also verify the significance of endogenous "threshold characteristics". Therefore, a single threshold model is established as follows:

$$TFEP_{it} = \mu_i + \omega_1 lnET_{it} \times I(lnpGDP_{it} \leq \gamma) + \omega_2 lnET_{it} \times I(lnpGDP_{it} > \gamma) + \omega X_{it} + \varepsilon_{it} \quad (2)$$

In Equation (2), the meanings of dependent variable, core explanatory variable and each control variable are the same as above. The threshold variable in the model is expressed by the level of economic development $lnpGDP$, ω is the corresponding coefficient vector, and

γ is the threshold value. The formula also contains an index function $I(\bullet)$, whose value is 1 when the corresponding condition holds, otherwise is 0. $\varepsilon_{it} \sim idd(0, \delta^2)$ is the random interference. Moreover, once the model passes the double threshold test, the following equation can be set up.

$$TFEP_{it} = \mu_i + \omega X_{it} + \omega_1 lnET_{it} \times I(lnpGDP_{it} \leq \gamma_1) + \omega_2 lnET_{it} \times I(\gamma_1 < lnpGDP_{it} \leq \gamma_2) + \omega_3 lnET_{it} \times I(lnpGDP_{it} > \gamma_2) + \varepsilon_{it} \quad (3)$$

It should be noted that, in the above formula, $\gamma_1 < \gamma_2$ and the meanings of other indicators are consistent with that of formula (2).

3.3 Variable description

The explained variable: Total factor ecological efficiency $TFEP$. In this paper, a super efficiency SBM model considering non-expected outputs is adopted to measure total factor ecological efficiency which can effectively avoid the problem of 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. At the same time, this paper selects a non-directed super-efficiency SBM model and constructs an adjacent reference Malmquist index (Adjacent Malmquist). In the choice of input and output indicators, referring to researchers such as Yan et al. (2020) and Shen et al. (2020), the paper creatively adds the ecological footprint measured by the improved energy-ecological method (Yang and Zhu 2016; Tan and He 2016).Table 1 shows the inputs of various biological accounts and energy accounts and the elements of input-output listed in Table 2 are selected after careful consideration in the study.

Table 1 The index table of input and output

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

Table 2 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

Core explanatory variable: Energy technology innovation *lnET*. This study divides energy technology innovation into two categories, including the advancement of fossil fuels technology and the research on the exploitation and application of clean energy technologies (Sagar, 2004). According to the reality in China, the innovation in energy technology of new energy technology research is mainly manifested in the technological innovation of non-fossil energy (such as the energy of wind, ocean, biomass energy, etc.), while the technological innovation in the original energy system is mainly reflected in the improvement and breakthrough of technologies such as energy conservation and pollution reduction (Guo 2013). On this basis, this paper gives a comprehensive definition of energy technology transformation from the two angles of technology innovation in new energy utilization and technology innovation in energy save and emission discharge. Drawing on the practices of Ye (2018), Fan (2020) and Li and Lin (2016), the number of patent applications for "non-fossil

energy (new energy and renewable energy)" and the number of patent applications for "energy saving and emission reduction" respectively represent the two aspects of energy technology innovation described above.

Threshold variable: Economic development level $lnpGDP$. Drawing lessons from existing research, this article uses the deflated regional real per capita gross domestic product to evaluate the threshold variable of the economic development level after it is processed logarithmically.

Control variables: Capital affluence Cap is represented by the ratio of the industrial sector's equity to GDP; Population density Pop is manifested by the ratio between the total number of permanent residents in the region at the end of the year and the area under the jurisdiction of the province (Qiu and Zhou 2020); Environmental regulation Reg is indicated by the proportion of completed pollution control in GDP (Wang 2016); Degree of openness Fdi. Since foreign direct investment can affect the environment and regional economy through technology spillovers or knowledge spillovers and pollution transfer effects (Ma 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 neighbors, this study establishes a 0-1 adjacency matrix. In particular, when two spatial decision-making units have a common boundary, it is 1, otherwise it is 0. The significance of 0-1 spatial weight matrix lies in that only when two regions are adjacent can certain spatial correlation occur. In the matrix construction, it is assumed that Hainan Province and Guangdong Province have the condition of being adjacent to Rook. The matrix is set up as follows:

$$\omega_{ij} = \begin{cases} 1, & \text{region } i \text{ is adjacent to region } j \\ 0, & \text{region } i \text{ and region } j \text{ are not adjacent} \end{cases} \tag{4}$$

3.4 Data source

Setting the year from 2000 to 2017 as the research period, this paper selects 30 mainland regions in China as the research data. Due to the obvious data missing in Hong Kong, Taiwan, Tibet and Macao, we have eliminated them. The total factor ecological efficiency data processed in this paper are nearly obtained from *China Statistical Yearbook* and *Wind - Economic Database*; The data of energy technology innovation came from the public patent database retrieved by *Shanghai Intellectual Property (Patent) Public Service Platform.* In the specific operation, the search scope is positioned at "non-fossil energy" and "energy conservation and emission reduction" technologies. The abstract and keywords are set as "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, the specific types of patents are set as invention patents and utility model patents after excluding design patents; The consumption of various types of energy are mainly from *China Energy Statistical Yearbook*, *National Energy Model Integration Platform of Beijing Institute of Technology* and various public statistical information; The data of economic development level and control variables stem 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.*

In order to avoid the lack of credibility and comparability of the data caused by price

fluctuations, the paper sets the base period as 2000, deflates the prices of all monetary quantities, and adjusts them to comparable prices by means of a basket of price indexes such as fixed asset investment price indexes. Moreover, for fear of the heteroscedasticity and multicollinearity, the logarithm processing is carried out on the related variables. Table 3 shows the specific descriptive statistical results of the correlation coefficient matrix of each variable.

Table 3 The descriptive statistics of each variable

Variable	Mean	Variance	Max	Min
TFEP	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

4. Empirical analysis of energy technology innovation on China's total factor ecological efficiency

4.1 Estimation result of the spatial econometric model

4.1.1 Spatial correlation test

Before proceeding with the specific selection and application of the spatial measurement model, the spatial correlation analysis of economic activities should be carried out first, which usually adopts Moran index, Lagrange multiplier form LMLAG, LMERR and its robust form Robust-LMLAG, Robust-LMERR test, etc. In this study, Moran's index is firstly adopted to examine whether the target data is spatially dependent, and then Lagrange multiplier form and

spatial effect decomposition are applied to make a more comprehensive judgment. Specifically, the Moran index is defined as follows:

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\overline{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{5}$$

Secondly, in order to make up for the shortcomings of the global Moran index measurement, this paper introduces the Moran scatter diagram and Lisa cluster diagram, which are the local spatial correlation test indexes, so as to concretely analyze the spatial distribution characteristics within 30 provinces. The following is the definition of the local Moran index (Moran P A 1950).

$$Local\ Moran's\ I = \frac{n^2}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{(x_i-\bar{x})\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_j-\overline{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{6}$$

Table 4 displays that both the provincial total factor ecological efficiency and energy technology innovation in China present an obvious spatial correlation on the whole, especially in recent years, the positive spatial correlation is more obvious. Meantime, the variation trend of Moran Index in different years is not consistent, indicating that the inter-provincial total factor ecological efficiency and energy technology transition in China are greatly affected by the spatial distribution, showing an evident spatial cluster feature. Figure 1 and Figure 2 respectively express the partial Moran scatter plots of the mean total factor ecological efficiency and mean energy technology innovation during the sample period. It can be seen the first and third quadrants alone cover most of the points, indicating that both exhibit the feature of "high-high" aggregation (Beijing, Tianjin, Shanghai and other provinces) and "low-low" aggregation (Qinghai, Xinjiang, Yunnan and other mid-west regions), suggesting that province of internal efficiency level with strong spatial similarity.

Table 4 Spatial correlation test

	TFEP	*lnET*

Year	Moran	Z-score	Moran	Z-score
2000	-	-	0.000	0.287
2001	0.451***	3.934	0.081	0.950
2002	0.280***	2.533	0.097	1.084
2003	-0.043	-0.066	0.028	0.530
2004	0.028	0.507	0.078	0.934
2005	-0.062	-0.232	0.052	0.718
2006	-0.090	-0.489	0.115	1.232
2007	0.279***	2.637	0.160*	1.586
2008	-0.038	-0.031	0.168**	1.653
2009	0.074	0.894	0.198**	1.903
2010	0.166**	1.653	0.217**	2.051
2011	0.187**	1.886	0.293***	2.687
2012	0.238***	2.323	0.266***	2.437
2013	0.204**	2.030	0.217**	2.049
2014	0.185**	2.001	0.253***	2.355
2015	0.148**	1.661	0.293***	2.644
2016	0.169**	1.962	0.270***	2.463
2017	0.071	0.970	0.213**	2.009

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

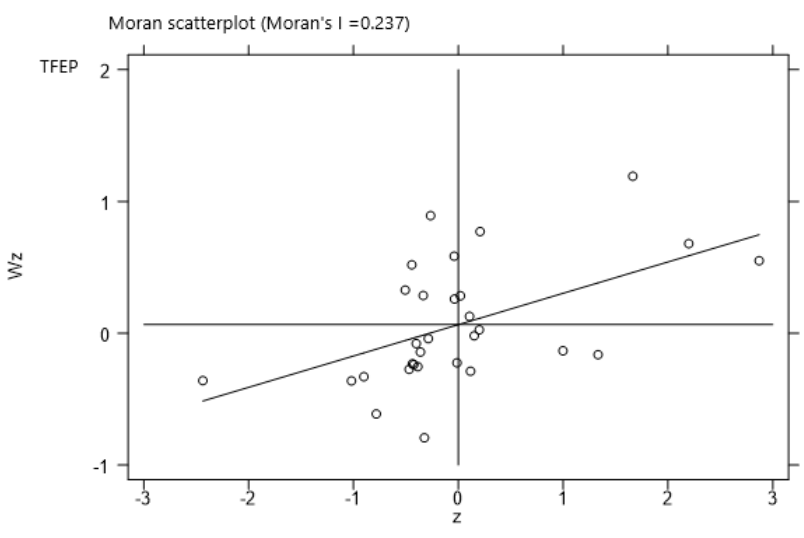

Fig.1. The Moran scatter plot of total factor ecological efficiency

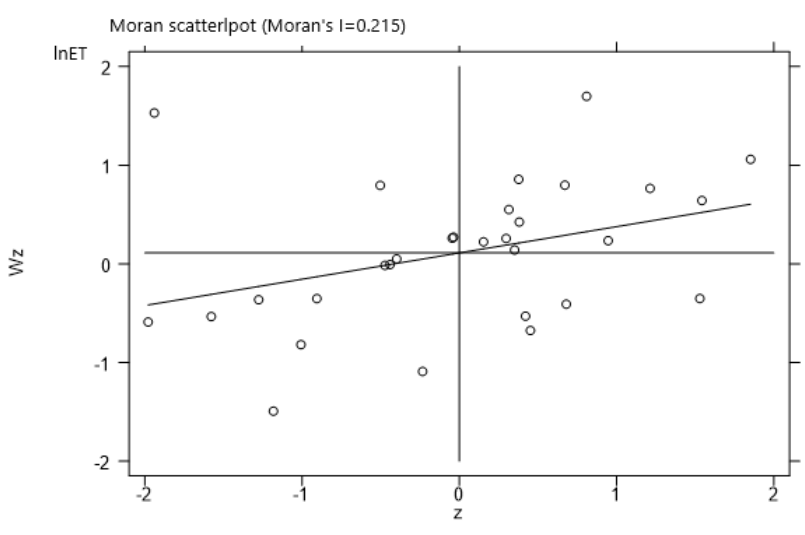

Fig.2. The Moran scatter plot of energy technology innovation

Actually, Moran index test is a preliminary test of spatial dependence and heterogeneity of total factor ecological efficiency. Before the formal analysis of spatial measurement models, we also need to estimate the non-spatial panel models and examine their statistics, that is, the existence of spatial correlation should be further judged by LM test. In this paper, OLS, spatial fixed effect model, time fixed effect model and spatial and temporal fixed effect model are all combined for model estimation (Xiao 2018), and Table 5 summarizes the results for several types of models. According to the LM test and the significance level of the robust LM test of the four panel models, it is found that there is indeed a large bias in the traditional panel model which is non-spatial. Instead, it remains essential to establish the spatial econometric model. Furthermore, following Lagrangian test and judgment rule, we should pay close attention to the results of the spatial lag model (SLM).

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

Note: 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.

4.1.2 Empirical results of spatial Durbin model

Wald test and LR test are two indispensable parts to conduct the spatial econometric model. They are adopted to severally examine the possibility that the spatial Durbin model can degenerate into SLM or SEM under the condition that the model results vary greatly due to the different types of models. If both test results reject the null hypothesis, it can be considered that SLM or SEM cannot be selected. Hereby, the spatial Durbin model is finally conducted in this paper. In the selection of specific effects, models of specific effects are considered through the test Hausman and LR. In line with Table 6, the three test statistics have passed the 1% significance level test, showing an invalid original hypothesis. Therefore, we finally choose to establish the dual fixed-effect spatial Durbin model.

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

It can be concluded from Table 7, in the three types of spatial Durbin model with different effects, the spatial lag coefficient ρ of the dependent variable is significantly positive, which further proves the positive spatial correlation of the regional total factor

ecological efficiency. As far as the internal regions are concerned, the influence of energy technology patent $lnET$ on total factor ecological efficiency $TFEP$ presents a U-shaped pattern, showing a change from negative to positive. Capital affluence Cap exerts an effectively positive force on total factor eco-efficiency, while population density Pop has an adverse impact to some extent; From a spatial perspective, by integrating $Wx * lnET$ and $Wx * (lnET)^2$, it is easy to find an apparent spatial effect between the patents of energy technology innovation and regional green development, which also displays a U-shaped change. Notably, the spatial influence coefficients are greater than those within the region, which are -0.276 and 0.021, respectively. In terms of the four control variables, except for the level of environmental regulation Reg, other variables all demonstrate significant spatial influence.

Table 7 The results 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	0.000	-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	

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

Due to the fact that one of the main features of spatial Durbin panel model is the spatial rebound effect between variables, relying solely on the influence of variables and their lagged items can not fully reflect their spatial correlation. More critically, we focus on the spatial decomposition effect of explanatory variables on explained variables after treating the spatial econometric model with partial differentiation, including direct effect, spillover effect and the total effect of both. Among them, the direct effect includes the spatial feedback cumulative effect of the spillover effect of the province to its neighboring provinces, that is, it includes the feedback effect of the spillover effect of its own province and the spillover effect of the neighboring provinces (Yuan et al., 2020); The indirect effect refers to the spillover effect, that is, the spatial diffusion of the influence of the province on the neighborhood. And the total spatial effect covers the previous two types of effects in a given province, but it is not simply a summation.

Table 8 demonstrates the spatial effect decomposition results of both short term and dynamic long term. The following is the concrete analysis. ①In terms of direct effect, the level of technological innovation within the region has a non-linear U-shaped relationship with the provincial total factor eco-efficiency, that is, the number of energy technology patents has different influences on the green productivity in various areas. In view of the coefficient, every 1% change in the weighted number of the energy technical innovation in the early stage will reduce the regional total factor ecological efficiency by 0.073%, while it will increase 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 has no obvious

change, but the influence coefficient is larger, manifesting that the long-term influence is stronger;②In terms of indirect effect, the overflow influence of energy technology innovation on ecological efficiency in external regions also has a U-shaped relationship, which is consistent with the above analysis results and provides empirical support for Hypothesis 1. In the long run, the spatial effects are greater than the short-term spillover effects, which are -0.392 and 0.030 respectively. In addition, the inter-regional impact coefficients of energy technology innovation are all greater than its direct effect coefficients, indicating that the spatial indirect effect of energy technical patents cannot be ignored;③In terms of the total effect, Since energy technology innovation has the same influence on total factor ecological efficiency in direct and indirect effects, its cumulative total effect is a larger with a more significant level. Similarly, the spatial total effect shows a significant U-shaped effect, which verifies the first half of hypothesis 2 in this paper. In general, the spatial impact of energy technology innovation level on total factor ecological efficiency reflects a significant U-shaped relationship with a stronger spatial spillover effect, and emerges as a stable long-term shock.

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
	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
Total	*Reg*	-8.305	-0.500	-9.160	-0.500
effect	*Fdi*	0.111**	1.990	0.123**	1.990

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

4.1.3 Robustness test

In the spatial panel, an appropriate spatial weight matrix is the key factor for the success of model building. The results may differ significantly depending on the type of matrix. In consequence, this paper selects two spatial weight matrices concerning the geographic distance and information distance as a robustness test of the model, so as to provide evidence for the credibility and stability of the above empirical results of spatial Durbin model and its decomposition effects. Table 9 collects the models of two types of robustness tests, which are conducted on the basis of double fixed SDM models. The results show that the number of significant variables and the influence direction of variable coefficient are the same as the results in this paper. Moreover, there is no contradiction between the three kinds of effects and the above conclusions, and the spatial effect coefficient is even larger, manifesting that the model establishment is more rational.

Table 9 SDM robustness test

Matrix type		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	

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

4.2 Estimation result of the threshold panel model

4.2.1 Empirical results of threshold panel model

On account of theoretical analysis and statistical analysis, it can be seen that the core for the non-linear relationship between energy technology innovation and total factor ecological efficiency lies in the intervention of intermediate mechanism. In light of the extremely uneven development of various provinces in China, this study empirically explores the complex mechanism among the innovation in energy technology and regional total factor ecological efficiency under the heterogeneous level of economic development in different areas. In the threshold model, the F value and the corresponding self-sampling P value are obtained after 400 repeated sampling, as demonstrated in Table 10. Based on the value of P in the Table 10, it can be judged that the model not only passes a single threshold, but also has a second threshold. In other words, it is highly possible to have a double threshold effect of economic development level, with two thresholds 9.0933 and 9.5651. Consequently, this paper will analyze the double threshold effect in detail.

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
trible	11.630	0.880	37.319	38.668	55.505

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

To acquire the threshold and the confidence interval in a more intuitive way, we further identify the threshold value by feat of the least square likelihood ratio statistic LR. The threshold estimate is the statistic when LR is zero. Figure 3 presents the likelihood ratio function graphs covering the two threshold values respectively.

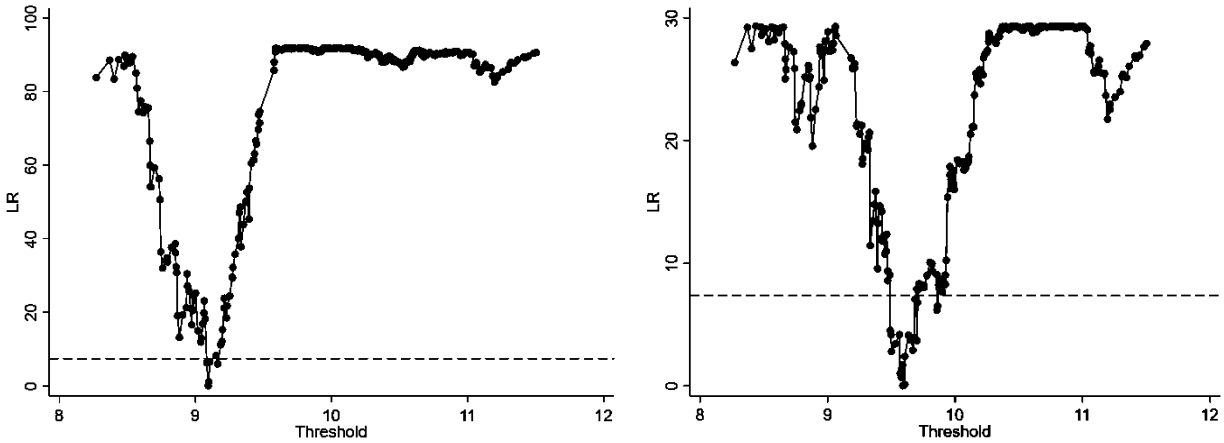

Fig.3. The function graphs of Likelihood ratio of two threshold values (a) and (b)

Table 11 presents the two existing thresholds and their confidence intervals of the threshold model which are obtained through software analysis. In combination with Figure 3, it is easy to find that the threshold values at the 95% confidence level are respectively [9.0626, 9.1199] and [9.4934, 9.5788], and all the LR values are less than the critical value of 7.35 which is 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	9.093 3	[9.062 6, 9.119 9]

Double threshold	9.565 1	[9.493 4, 9.578 8]

In accordance of the threshold regression, it is concluded that the driving impact of energy technology patents on total factor eco-efficiency is not monotonically incremental (or degressive). The effect coefficient of energy technology innovation varies evidently in different provinces, that is, as the economic development level continues to increase, it will first inhibit the regional total factor ecological efficiency and then have a completely opposite effect. To a certain extent, it is consistent with the "U" shaped curve in spatial Durbin model with the addition of spatial lag term and spatial direct effect. Specifically, when the level of economic development is lower than 9.0933, every 1% optimization of energy technology innovation will lead to a 0.056% decrease in the level of green economy; When the value of per capita income crosses the first threshold, that is, when the $lnpGDP$ is between 9.0933 and 9.5651, the direction of the influence of energy technology patents on the regional total factor ecological efficiency changes structurally. The effect coefficient changed from negative to positive, while the parameter estimates does not pass the significance test; As the level of economic development continues to rise, its inhibitory effect is weakened, whereas not significant; Once the adjustment variable is greater than 9.5651, the elasticity coefficient of energy technology innovation activities turns to 0.017， passing the significance level test of 5%, which further validates the hypothesis 2 of this article. The above results illustrate that the optimal interval is the high value interval of the economic development level, at which point the energy technology innovation can raise the regional total factor ecological efficiency in a more productive way.

Table 12 The estimation results of the double threshold effect model

TFEP	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≤9.0933）	-0.056***	0.012	-4.630	0.000	-0.080	-0.033
lnET(9.0933<lnpGDP≤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

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

4.2.2 Robustness test

In order to avoid instability of the estimation, a robustness test is inevitably performed to examine the threshold effect of different types of energy technology innovation on total factor ecological efficiency. For this purpose, the energy technology innovation is divided into technology innovation for energy conservation and emission reduction of traditional energy $lnET1$ and technology innovation for comprehensive utilization of renewable energy $lnET2$. This paper conducts threshold regression for the two variables respectively, and the estimation are summarized in Table 13. It is not hard to find that for each type of energy technology innovations, no significant fluctuations have occurred in the value of the impact coefficient or the level of significance. More specifically，both the threshold effect and threshold value are similar to the above, and there is no apparent fluctuation in the measurement results of the control variables. On this basis, it can be considered that the threshold model constructed in this paper has good robustness.

Table 13 Robustness test of threshold model

Model	Model（1）		Model（2）	
TFEP	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
lnET1（*lnpGDP*≤9.0982)	-0.053***	-4.380		
lnET1(9.0982<*lnpGDP*≤9.5897)	-0.005	-0.510		
lnET1(lnpGDP>9.5897)	0.018**	2.350		
lnET2（*lnpGDP*≤9.0934)			-0.077***	-6.390
lnET2(9.0934<*lnpGDP*≤9.6052)			-0.009	-0.970
lnET2(*lnpGDP*>9.6052)			0.018***	3.010
cons	0.826***	15.100	0.847***	16.240

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

5. Discussion

Spatial econometric models indicate a significant U-shaped spatial impact between energy technology innovation and regional total factor ecological efficiency, among which the spillover effect between regions is more evident. The reason may lie in that although technology patent is a kind of intangible asset, the positive externality of knowledge and the mobility of human capital will facilitate the circulation and imitation of technology elements. In the short term, due to the immaturity energy technology, the region's own technology diffusion and technology reception capacity are very limited. At this time, the spillover technology elements can not bring positive learning and imitation between regions. On the contrary, due to the absorption of immature energy technologies which are not suitable for the region itself, the comprehensive economic benefits are not ideal as expected. In the long run, the energy technology matures into a viable technology, during which time the absorption capacity of the technology undertaking region is relatively strong. Under the premise of economic stability, the integration and imitation of different types of energy technology elements can further optimize industrial structure and improve the level of productivity, thus increasing the green ecological efficiency.

In accordance with the double threshold effects, it is easy to find that the relationship between energy technology innovation and regional total factor ecological efficiency also presents a U-shape, in which two inflection points exist. The probable reason may be that compared to pursuing green development goals, low-income areas concentrate on the improvement of economic aggregates. In this case, the effective application of energy technology could be prevented by both the conditions of energy application infrastructure and the investment environment of energy technology. Ulteriorly, energy technology innovation will exert an unfavorable influence on total factor ecological efficiency because of resource occupancy and capital crowding out effect; As the level of regional development reaches a certain level, its industrial structure becomes more reasonable. The economic development model characterized by intensification is more conducive to the consumption and development of non-fossil energy, and regional concepts of environmental protection and needs of green development fit into the achievements of energy technology innovation as well. In the mass, the development of energy technology innovation activities can reduce the innovation cost and effectively improve the level of cleaner production in such regions in all probability. Besides, 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". Thus, it will get the utmost out of the ecological protection advantages of carbon-free energy technology innovation and effectively promote the perfection of regional ecological efficiency.

6. Conclusions and suggestions

Considering STIRPAT model framework in the environmental economics, this study

explore the complicated effect of innovation in energy technology on the provincial total factor eco-efficiency in China. Using China's inter-provincial panel data and setting the research period as 2000 to 2017, this paper firstly adopts a requisite spatial correlation test and the spatial Durbin model which is based on three types of spatial weight matrices to probe both the short-term and long-term spatial relations of energy technology innovation and green economic development. As far as the spatial effect is concerned, we make a selective analysis of the spatial spillover effect of technology and verify hypothesis 1 successfully; Moreover, the mechanism of the nonlinear relationship between the two is further studied. Under the regulation of regional economic development level, this study investigates the sophisticated correlation between energy technology innovation and total factor eco-efficiency during the energy transition period, thus confirming the second hypothesis in Section 3. In short, the main conclusions of this paper are summarized as below ①Considering the ecological input, the total factor ecological efficiency appears positive spatial related among provinces in China, presenting the feature of "high-high" and "low-low" spatial agglomeration. At the same time, energy technology innovation, which covers energy conservation and emission reduction technologies of traditional fossil energy and development and utilization technologies of renewable energy, also appears apparent spatial dependence characteristics; ② Energy technology innovation has a significant spatial impact on the regional total factor ecological efficiency, whether it is a direct spatial effect, a spillover effect or a total effect, all present a "U"-shaped relationship, among which the effect of spatial spillover is stronger and the long-term effect is greater; ③ The influence of innovation activities in energy technology s on regional total factor ecological efficiency is characterized by a nonlinear shock with the

regional economic development level as the threshold. As the per capita income level of the region keep crossing the threshold value, the work form of energy technology innovation's effect on regional total factor ecological efficiency changes from prohibitive to acceerative. In the provinces with high level of economic development, energy technology innovation can prominently increase regional total factor eco-efficiency, while in the middle economic development interval, energy technology patents have not worked very well.

To raise the ecological efficiency is a key element to realize domestic green and sustainable development, thus ensuring to achieve China's international carbon emission reduction and carbon neutrality commitments. And to accelerate energy transition driven by the technology innovation is a key action to improve regional total factor ecological efficiency. For this purpose, this paper puts forward the following three suggestions. ①Collaborate to build an energy technology science and technology park, and promote the innovation model of industry-university-research cooperation. The agglomeration of new energy industry can make up for the lack of regional differences. Drified by capital and market advantages, the central city can play an innovative leading role in surrounding cities and realize the coordinated development of regional energy technology. Moreover, the industry can further accelerate the transformation of energy technology innovation achievements and boost the social and economic benefits of energy technology application through the cooperation with research institutes and universities; ② Coordinate the promotion of open innovation of energy technology and realize the regional application of cutting-edge energy technology. While improving the regional energy technology innovation capability, the spatial spillover effect of energy technology innovation on all-factor eco-efficiency is fully demonstrated

through inter-regional open innovation. By this mans, the absorption and transformation of cutting-edge energy technology can be effectively realized, so as to exert stronger impetus on innovation-driven regional low-carbon green economic development; ③ Create a new energy technology application environment and accelerate the intensive growth of the regional economy. Driven by the continuous development of regional economy, the government ought to take incentive measures to improve the clean energy infrastructure conditions, create a good market environment for the application and promotion of energy technology, raise the awareness of clean production in the region, thus gradually realize the coordinated development of energy-economy-environment system.

Appendix

Table 14 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,	Hebei, Inner Mongolia, Liaoning, Jilin, Fujian, Shandong	Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Guangdong

	Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang		
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 Yunnan and Gansu

Ethics approval

Not applicable

Consent for participate

Not applicable

Consent for publication

Not applicable

Conflict for publication

Not applicable

Conflict of interest

I declared that we have no conflicts of interest in this work.

Author Contributions

Conceptualization: [Li tuochen Shi Ziyi]; Methodology: [Shi ziyi Han dongri]; Software: [Shi Ziyi]; Writing-original draft: [Shi ziyi]; Writing-review and editing: [Shi ziyi Han dongri]; Supervision: [Li tuochen]

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Availability of data and materials

All data can be downloaded from China's National Bureau of Statistics.

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Figures

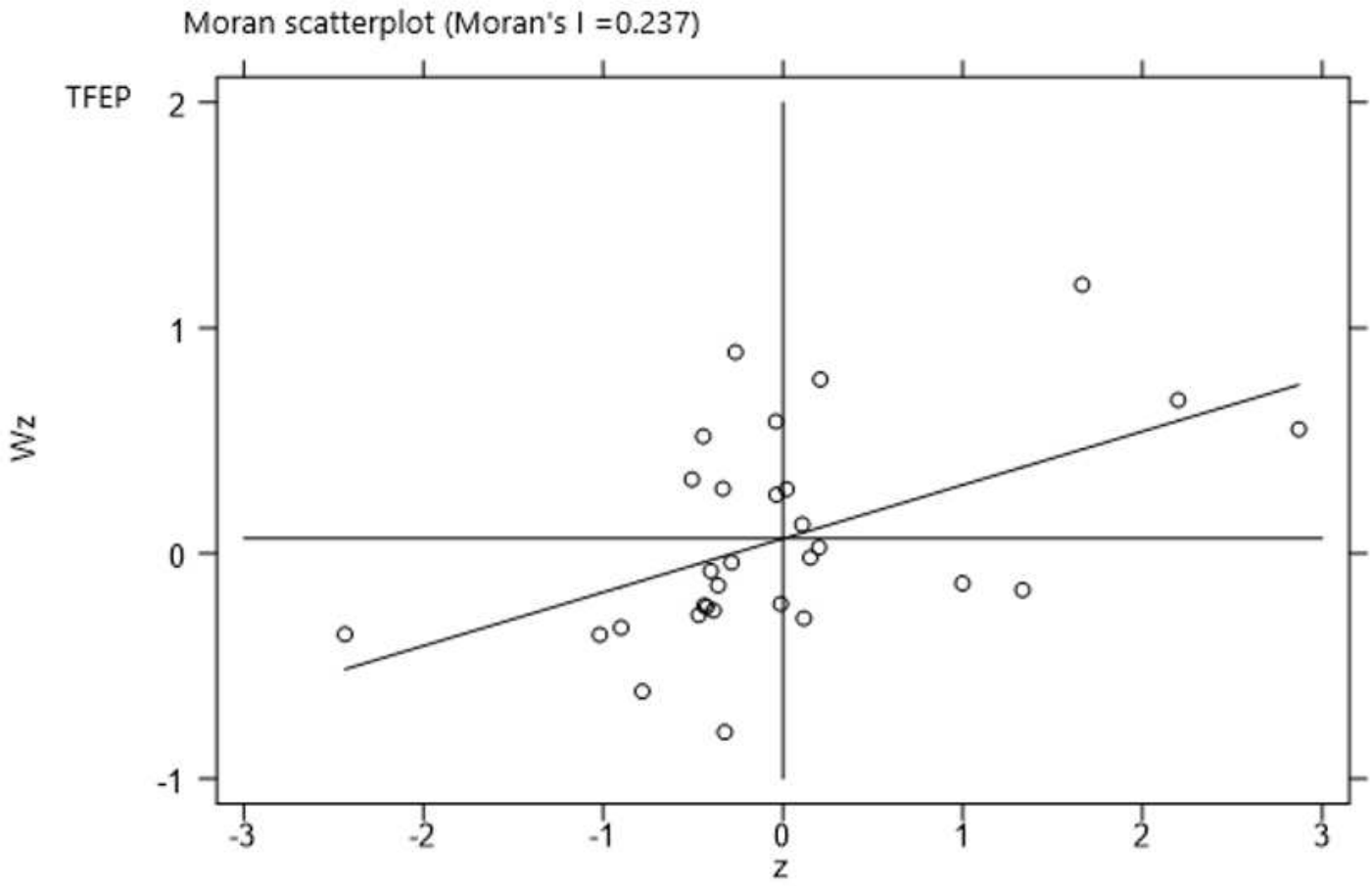

Figure 1

The Moran scatter plot of total factor ecological efficiency

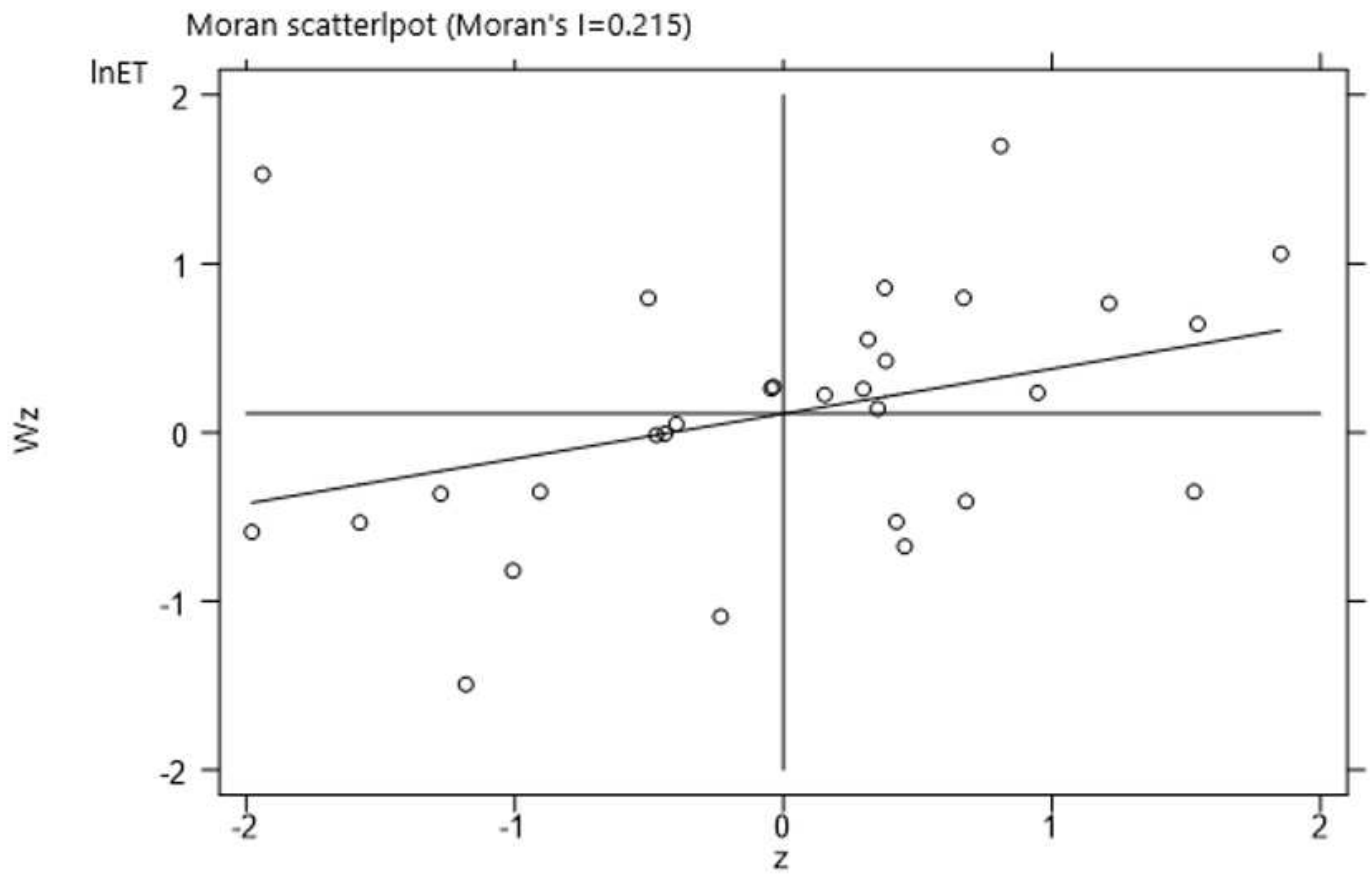

Figure 2

The Moran scatter plot of energy technology innovation

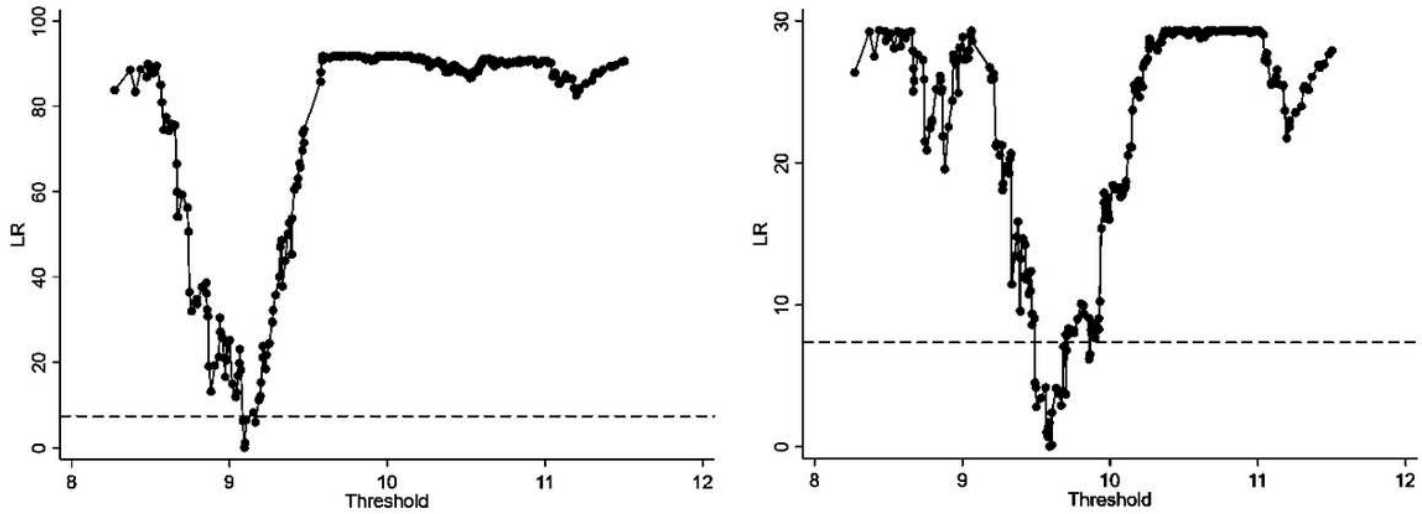

Figure 3

The function graphs of Likelihood ratio of two threshold values (a) and (b)