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RESEARCH ARTICLE

How the energy technology influences the total factor of energy efficiency?: evidence from China

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Abstract

Technological progress is of great importance to total-factor energy efficiency (TFEE). However, previous research has not narrowed technological progress into the energy field, generating rough and ambiguous empirical evidence for policymakers. In addition, technological progress is often discussed from a conventional perspective as a whole, ignoring its heterogeneity and spillover effect between regions. This study applies the stock of energy patents to reflect the effect of technological progress in the energy field on TFEE at first. The dynamic models are then employed to investigate if and how technological progress influences TFEE from the conventional and spatial perspectives for China's over the period of 2000–2016. The conventional analysis shows that energy technology is of great importance to TFEE. However, the creation-type of technology coming from businesses specifically is shown to have more success in enhancing TFEE than other types of energy technology. Further evidence coming from the spatial econometrics demonstrates that technology spillovers across regions are rather common and have significant effects on TFEE.

Keywords Total-factor energy efficiency (TFEE) · Energy technology · Spatial econometrics · China

Introduction

Over the past 40 years, China's economic growth has made remarkable achievements. In 2019, China's GDP reached 99.08651 trillion Yuan RMB and the GDP per capita was as high as 70,892 Yuan RMB (in price of 2019) (National Bureau of Statistics of China, NBSC 2020). People's living standards and production conditions have been greatly improved. However, simultaneously, the consumption of energy has also been increasing. According to the NBSC (2020), the average annual growth rate of energy consumption was 5.38% in 1978–2018. As early as 2018, China's energy consumption reached more than 4.5 billion standard coal equivalents, accounting for more than 20% of the world's total energy consumption (National Bureau of Statistics of China 2020). This high dependence on energy has brought about a series of energy security and environmental degradation, exerting adverse effects on China's high-quality economic development (Peters et al. 2007; Andrews-Speed 2009; Li et al. 2015; Chen et al. 2021; Huang et al. 2021). Judging from the current macroscopic situation in China, the energy demand pattern is still expected to undergo an increase (Liu et al. 2016; Cheng et al. 2020). To cope with these increasingly serious problems, a new round of energy regulations is in full effect. As early as 2014, China pledged to reach a peak in carbon dioxide emissions in the "U.S.-China Joint Announcement on Climate Change." In addition, this target has been written into the 2021 government work report. Since China is ranked 73rd globally regarding energy efficiency, the continuous improvement of total-factor energy efficiency (TFEE) has become one of the most effective manners for China to fulfil this target while keeping its competitiveness worldwide (Andrews-Speed 2009; Du et al. 2019; Wu et al. 2021).

The drivers of TFEE have been extensively explored by lots of previous literature; such research clearly states that it is essential to depend on technological progress to improve TFEE (Zhao et al. 2014; Du et al. 2019; Long et al. 2020;

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Wu et al. 2021). Unfortunately, most of the existing literature has not narrowed technological progress to the energy field, therefore providing precarious and untargeted policy implications for their readers (Aydin and Esen 2018; Wei et al. 2020; Wu et al. 2021). Since the research and development (R&D) is recognized as a crucial driver of improving TFEE, previous literature has reported that the more inputs of R&D, the higher TFEE will be (Aydin and Esen 2018; Lin and Zhu 2021). However, technology innovation is a difficult process that not only relies on the amounts of R&D input but also highly depends on the experience of research personnel and the quality of R&D equipment. Therefore, some of the R&D inputs will not lead to new technology. In addition, not all R&D inputs are related to the field of energy, and only R&D related to the energy field will exert a significant effect on TFEE. As a result, it is inadequate to operationalize R&D as an effective instrument in improving TFEE even if it has been found that R&D is positively related to TFEE improvement through empirical analyses.

Moreover, there exists significant heterogeneity in different kinds of energy technologies; unfortunately, these are frequently discussed as a whole in the energy literature, and few of the existing studies have divided energy technologies according to their characteristics (Wang et al. 2012; Li and Lin 2016; Du et al. 2019). Organizations or institutions such as businesses, independent R&D institutions, or higher education institutions are the main sources of energy technology. The corresponding technology originating from these different sources will exert differentiated effects on TFEE because they have specific motivations and conditions. Similarly, the technology can also be distinguished according to its purposes (e.g., creation- vs utility-type), and it is essential to consider this heterogeneity when exploring how technological progress affects TFEE.

Accompanied by rapid improvements in economic growth, China has also made great progress regarding infrastructure, especially transportation infrastructures. Currently, China's different regions are easily and increasingly connected, and the business activities, especially technology transfers, of a region can easily influence those of other regions. The technological progress in one region may not only have important effects on its regional TFEE but also on its neighboring regions. To better understand how technology influences TFEE progress, it is essential to employ the available spatial econometrics to capture the spatial correlation characteristics, rather than utilize conventional linear analysis.

In response to the above three major drawbacks of the existing literature, this study first narrows the technological progress in the energy field, that is, we employ the energy patents as the proxy variable for denoting the effect of technological progress on TFEE. Second, the effect of technological progress on TFEE is not revealed from an overall perspective but rather is considered by distinguishing the energy patents from their sources and purposes. Third, to account for the energy technology spillovers across regions, we employ spatial econometrics to explore whether energy technological progress has spatial spillovers regarding TFEE.

We organize the rest of this paper as follows: Related literatures from the perspective of the factors influencing TFEE are shown in the "Literature review" section. The methodology of calculating the TFEE, data management, and empirical model in this study is presented in the "Research method, model construction, and data management" section. The empirical results are clearly presented and discussed in the "Results and discussions" section, and the final section identifies the corresponding conclusions and policy implications.

Literature review

Energy is one of the most important inputs of economic growth and the most substantial foundation on which people live and work. Accompanied by the growth of the population and economy in China, the demand for energy is constantly increasing, exerting significantly negative effects on sustainable development (Dauda et al. 2021; Long et al. 2021; Huang et al. 2022). Therefore, the continuous increase of energy efficiency has been employed as an important strategy to eliminate the contradiction between economic growth and energy consumption. According to the number of input and output factors, energy efficiency can be distinguished into a single energy efficiency and TFEE (Hu and Wang 2006). For the definition of the single energy efficiency, energy is recognized as the only input factor, and GDP is frequently taken as the only output factor. This definition has ignored other input factors (e.g., capital and labor) as well as other output factors (e.g. sulfur dioxide [SO_2] emissions). Despite this, the single energy efficiency has received increased attention in empirical research and policy regulations because it can be easily measured in practice (Huang et al. 2017; Aydin and Esen 2018). To address the drawbacks of the definition of the single energy efficiency, Hu and Wang (2006) have proposed the concept and framework of the TFEE. This framework is superior to conventional energy efficiency evaluations because it considers multiple input and output factors. Most of the literature that investigates the issues related to TFEE can be divided into two strands: the assessment methodology and driving factors for TFEE.

The assessment methodology for TFEE

The basic concept of assessing TFEE is to minimize the input factors under the condition that the amount of output is kept constant or to maximize outputs under the condition that the amount of input factors remains constant. Related measurement methods can be divided into parametric methods (represented by the stochastic frontier analysis method, hereinafter referred to as SFA) and non-parametric methods (represented by the data envelopment analysis method, hereinafter referred to as DEA). SFA is first proposed by Aigner et al. (1977) with the application of maximum likelihood estimation, assuming the existence of technical inefficiency, which is a major advantage of SFA. However, this pre-determined production function cannot reflect reality and or address the problem of multiple outputs. Unlike SFA, DEA does not require the advanced selection of the form of the production function (Zhan et al. 2016; Wu et al. 2019; Huang et al. 2022). DEA is especially capable of dealing with the situation of multiple inputs and outputs. Unfortunately, it suffers from the robustness problem because the random factors cannot be addressed. To improve the robustness of DEA, Song et al. (2013) have proposed the bootstrap DEA method, combining the DEA and bootstrap methods. Similarly, Kuosmanen (2012) has developed a new framework for DEA by incorporating SFA. With the promotion of application requirements and the development of new technologies, different types of DEA models have been developed, such as DEA based on the Malmquist index (Färe et al. 1994; Wang et al. 2013), a window function-based DEA model (Zhang et al. 2011; Vlontzos and Pardalos 2017; Sefeedpari et al. 2020), and a network DEA model (Fathi and Saen 2018).

The driving factors of TFEE

Technological progress and TFEE

The neoclassical economic growth theory posits that when the speed of technological progress reaches or even exceeds the speed of consumption of non-renewable resources, long-term economic growth can be expected (Stiglitz 1974). The endogenous economic growth theory similarly states that technological progress can achieve sustainable economic growth (Romer 1990; Twum et al. 2021). Regarding sustainable economic development, technological progress can reduce the input factors required for each output, which has been regarded as an important breakthrough in improving energy efficiency.

According to empirical studies, the enhancement of TFEE can be obtained through technological progress which is frequently denoted by R&D inputs or patents. For instance, based on a panel dataset of China's mining sector over the period 2004–2016, Lin and Zhu (2021) have reported that R&D expenditures can significantly enhance the TFEE of the mining sector. Similarly, Wei et al. (2020) have employed the feasible generalized least squares estimation to explore the effects of R&D as well as foreign direct investment (FDI) and trade on TFEE. They conclude that R&D activities promoted the TFEE of China's manufacturing sectors between 2000 and 2016. Based on a panel dataset covering the BRICS and the G7 countries over the period of 1993–2010, Camioto et al. (2016) found that patents are significant in improving the energy efficiency of the BRICS countries (Brazil, Russia, India, China, and South Africa).

Compared to the R&D inputs, the patents are considered the outputs of the R&D activities. The energy patents contain a great deal of information on the nature of creation and are frequently employed as a more popular proxy variable for denoting the effect of technological progress in the energy field (Wang et al. 2012; Du et al. 2019; Huang et al. 2021). Additionally, they can be classified into different types and provide more details for the policymakers. However, similar to the total R&D, not all patents are related to the energy field and only a few of them will serve as impetus to drive TFEE. Therefore, it is also essential to narrow the patents in the energy field to provide more credible and targeted evidence for policymakers regarding how technological progress influences TFEE.

Other influencing factors of TFEE

Apart from technological progress, a wide range of influencing factors, such as industrial structure optimization, energy price, and the level of openness, has frequently been identified as drivers of TFEE in empirical literature.

Industrial structure optimization is able to reflect the coupling degree of input–output factors among different industrial sectors (Luan et al. 2021). It aims to pursue the maximum economic benefits by optimizing the allocation of resources (such as labor, energy, and capital). When an economy has higher levels of industrial structure optimization, it will usually have the same output with less input factors. Consequently, industrial structure optimization is always an important driver of improving energy efficiency. The relationship between industrial structure optimization and energy efficiency has been frequently explored in empirical studies which have captured that energy efficiency improvement can be obtained through optimizing the industrial structure. For instance, Luan et al. (2021) have reported that industrial structure optimization can significantly increase China's energy efficiency between 1997 and 2016.

The traditional price theory shows that the price of products is the market signal that reflects the relationship of the demand and supply of a product. Since there is a substitution relationship among different kinds of input factors, the price of energy not only determines the demand for energy but also influences the demand for other input factors such as labor and capital. Therefore, the evolution of energy price will influence the relative ratios of different kinds of factors and energy efficiency. In empirical studies, both Fan et al. (2007) and Zhao et al. (2014) have captured solid evidence that the enhancement of energy efficiency can be obtained through a quicker rise in energy prices.

Additionally, openness comprising FDI and trade is also recognized as an important factor influencing TFEE. According to Grossman and Krueger (1991), the environmental performance of the host country will be affected by trade and FDI; however, this relationship will be complicated. First, openness can influence the industrial structure adjustment of the host country; this is called the structural effect. Second, openness also enhances the scale of production, thus exerting scale effects on TFEE. Lastly, advanced technologies of the developed country embodied in trade and FDI can be transferred to the host country, formulating the technology effect on TFEE. In this paper, FDI and trade are respectively taken as the proxy of reflecting the effect of openness on TFEE.

Research method, model construction, and data management

Research method

The super-efficiency slacks-based measure model

Among the non-parametric estimators, DEA has gained popularity in empirical studies because it can be employed in both multi-input and multi-output scenarios. Unfortunately, some unexpected outputs, such as SO_2 emissions, will also be produced during this economic production process, and the conventional DEA cannot include undesirable outputs and is unable to determine the relaxation of input and output. Compared to DEA, the slacks-based measure (SBM) model provides unbiased efficiency estimates of the decision-making units (DMUs) which are neither oriented nor radial and have been proven effective in such cases (Tone 2001; Wang and Feng 2015). In this study, we employed the SBM to estimate TFEE. To help the readers better understand the framework of SBM, we provide a brief introduction for the SBM when the undesirable outputs are considered.

Assuming that there are DMUs with the number of M, and each has N inputs, S_1 and S_2, respectively, stand for the desirable and undesirable output.X, Y^g, and Y^g are matrices, expressed with the following forms:

$$\begin{cases} X = [x_1, x_2 \ldots\ldots x_n] \in R^{m\times n} \\ Y^g = [y_1^g, y_2^g \ldots\ldots y_n^g] \in R^{S_1\times n} \\ Y^b = [y_1^b, y_2^b \ldots\ldots y_n^b] \in R^{S_2\times n} \end{cases} \tag{1}$$

In addition, we assume that the slack of input, desirable output, and undesirable output are S^-, S^g, and S^b, respectively. Under the constant returns to the scale condition, the SBM-undesirable model can be expressed as follows:

$$p = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left[\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right]} \tag{2}$$

$$\text{where } s.t.\begin{cases} x_0 = X\lambda + S^- \\ y_0^g = Y^g\lambda - S^g \\ y_0^b = Y^b\lambda + S^b \\ \lambda \geq 0 \\ S^g \geq 0 \\ S^b \geq 0 \end{cases} \tag{3}$$

While the above conventional SBM model is able to evaluate the efficiency evolution when the undesirable outputs exist, it suffers from a loss of information. To address this drawback, the super-efficiency model has been introduced to the SBM framework by Tone (2004), forming the super-efficiency SBM model:

$$p^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{i0}}}{1 + \frac{1}{s_1+s_2}\left[\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right]} \tag{4}$$

$$s.t.\begin{cases} \bar{x} \geq X\lambda \\ \overline{y^g} \leq Y^g\lambda \\ \overline{y^b} \geq Y^b\lambda \\ \lambda \geq 0 \\ \bar{x} \geq x_0 \\ \overline{y^g} \leq y_0^g \\ \overline{y^b} \geq y_0^b \end{cases} \tag{5}$$

where p^* denotes the efficiency value of the DMU. Other variables share the same meanings as shown in Eqs. (2) and (3).

Dynamic spatial Durbin model

As argued by Elhorst (2014) and Gilio and Moraes (2016), when there are spatial correlations, the conventional analysis may obtain biased estimates. The spatial econometrics, which includes the spatial terms, is able to provide unbiased empirical results for this case. There are three major kinds of constructions for spatial econometrics comprising the spatial lag model (SLM), spatial error model (SEM), and spatial Durbin model (SDM). Since the SDM can be recognized as a combination of SLM and SEM and provides more details explaining the evolution of TFEE, we employed it in our empirical analysis.[1] In addition, TFEE usually demonstrates a strong intra-continuity over periods of time, and the dynamic model is able to capture this information better than the static model. Consequently, the dynamic spatial Durbin model (DSDM) was employed, expressed as:

$$\begin{aligned} \ln\ TFEE_{i,t} &= \beta_0 + \theta\ \ln\ TFEE_{i,t-1} + \rho W\ \ln\ TFEE_{i,t} + \lambda W\ \ln\ TFEE_{i,t-1} \\ &+ \sum_{i=1}^{N} \beta_i\ \ln\ X_{i,t} + \sum_{i=1}^{N} \gamma_i W\ \ln\ X_{i,t} + \mu_i + \varsigma_{i,t} \end{aligned} \tag{6}$$

where $TFEE$ stands for the total-factor energy efficiency obtained by the super-efficiency SBM model. $\boldsymbol{X}$ denotes the vector matrix that includes the key independent variable and control variables, and $\boldsymbol{\beta}$ is the corresponding vector matrix of $\boldsymbol{X}$. $\boldsymbol{\theta}$, ρ, and λ, represent the time autoregressive coefficient, the spatial autoregressive parameter, and the spatial-time autoregressive parameter, respectively. W is a predetermined spatial weight matrix that is employed to measure the spatial relationship among regions. There are two major kinds of spatial weight: the binary weight matrix and the distance weight matrix. Considering that the binary weight matrix only captures the spatial relationship of neighboring regions, and the weights for reflecting the degree of the spatial relationship are assumed to be the same, the distance weight matrix[2] was applied, shown as:

$$w_{i,j} = \begin{cases} 0 & when\ i = j \\ \frac{1}{d_{i,j}} & when\ i \neq j \end{cases} \tag{7}$$

where w is the spatial weight of W. $d_{i,j}$ stands for the distance measured by railway mileage between the capitals of province i and j.

Selection of independent variables for the empirical model

Since there are no official statistics on the R&D related to specifically the energy field, the energy-conservation patents which aim to save energy are employed as proxy variables for denoting the effect of the technological progress in the energy field on TFEE. However, the number of energy patents only reflects the volume but not the quality of the technology in the energy field. In addition, depreciation and diffusion, which are universal for energy patents, cannot be reflected through the number of energy patents. Consequently, the stock of the energy patents, which is based on the framework of Popp (2002), is employed as the proxy variable for denoting the effect of energy technology on TFEE, shown as:

$$SPAT_{i,t} = \sum_{j=0}^{t} PAT_{i,j} \exp[-\delta(t-j)] \cdot \{1 - \exp[-\gamma(t-j)]\} \tag{8}$$

where $SPAT$ denotes the stock of energy patents, PAT represents the number of energy-conservation patents, and t stands for the period of time. δ and γ, respectively, denote the depreciation and diffusion rates. Similar to Lin and Zhu (2019), δ and γ are respectively assigned to be 36% and 3%. However, there is significant heterogeneity among different kinds of energy patents. For the patents with high technical content, which are not easily outdated, the corresponding depreciation rates for these patents are lower compared to those patents with low technical contents. To further distinguish the energy patents, we assigned different depreciation rates for different kinds of patents[3] Lastly, it is noteworthy that 1995 is set as the base period for calculating the stock of energy patents.

As mentioned in the "Literature review" section, since industrial structure optimization aims to obtain the maximum ratio of output to input by allocating the input resources, it is important to TFEE. In the current research, we employ the Theil index to describe the degree of the industrial structure optimization, expressed as:

$$TLL = \sum_{i=1}^{N} \frac{Y_i}{Y} \ln \left[\frac{Y_i}{L_i} \Big/ \frac{Y}{L} \right] \tag{9}$$

where TLL stands for the Theil index as well as industrial structure optimization in this study. Y and L denote the output and labor inputs, respectively. $i = 1, 2, 3$ denotes the primary, secondary, and tertiary industries. The higher the Theil index, the lower the optimization degree of the industrial structure.

As there is a substitutional relationship among different kinds of input factors, when the price of one input factor increases (e.g., energy price), the inputs of other resources, such as labor or capital, will be influenced, exerting significant effects on the changes of the input–output ratio. Therefore, the evolution of the energy price will also have significant effects on TFEE.

In addition, China's state-owned enterprise has a congenital advantage in achieving resources; however, part of the input factors is not yet configured according to the market dynamic, and the misallocation of resources is a very common phenomenon for state-owned enterprises. Consequently, the input–output ratios of economic activities for state-owned enterprises are usually higher than non-state enterprises. Considering that the reform of China's state-owned enterprise has played a leading role in

[1] The *Wald* test is also applied to determine which kind of spatial model is the best fit for our estimations.

[2] The distance between different provincial regions is defined as the train mileage between the provincial capitals among provinces.

China's economic system reform, it is also considered an important factor influencing TFEE.

Based on the above information, we present the empirical model for TFEE as:

$$\ln TFEE_{i,t} = \alpha + \beta_1 \ln SPAT_{i,t} + \beta_2 \ln FDI_{i,t} + \beta_3 \ln TLL_{i,t} + \beta_4 \ln SOE_{i,t} + \beta_5 \ln EP_{i,t} + \beta_6 Policy_{i,t} + v_{i,t} \tag{10}$$

where *TFEE* denotes the total-factor energy efficiency. *SPAT*, *FDI*, *TLL*, *SOE*, and *EP*, stand for the energy technology, foreign direct investment, industrial structure optimization, the reform of China's state-owned enterprises, and the energy price, respectively. Considering that China implemented an energy efficiency improvement policy in 2005, and to examine whether this policy has important effects, we also introduced a dummy variable (*Policy*) demonstrating this policy (i.e., the year dummy variables between 2000 and 2005 are set as 0 and others are set as 1). The subscripts i and t denote province and year, respectively. α and $\beta_i (i = 1.2, \ldots, 6)$ are the coefficients that need to be estimated. The error term is written as ε_{it}.

After we considered the effect of energy technology from its source and purpose on TFEE, the corresponding empirical models are shown as:

$$\ln TFEE_{i,t} = \beta + \delta_1 \ln BPAT_{i,t} + \delta_2 \ln IPAT_{i,t} + \delta_3 \ln OPAT_{i,t} + \delta_4 \ln FDI_{i,t} + \delta_5 \ln TLL_{i,t} + \delta_6 \ln SOE_{i,t} + \delta_7 \ln EP_{i,t} + \delta_8 Policy_{i,t} + v_{i,t} \tag{11}$$

$$\ln TFEE_{i,t} = \lambda + \eta_1 \ln CPAT_{i,t} + \eta_2 \ln UPAT_{i,t} + \eta_3 \ln FDI_{i,t} + \eta_4 \ln TLL_{i,t} + \eta_5 \ln SOE_{i,t} + \eta_6 \ln EP_{i,t} + \eta_7 Policy_{i,t} + v_{i,t} \tag{12}$$

Model (11) distinguishes the energy technology from its sources: businesses (*BPAT*), independent research institutions (*IPAT*), and others *(OPAT)*. Model (12) divides energy technology according to its purposes: creation- (*CPAT*) and utility-type (*UPAT*). Other variables share the same meanings as shown in Model (10). For simplicity, we did not show the corresponding DSDM for the TFEE.

Data source and management

Considering that we cannot obtain the data on Tibet, the other 30 provincial regions in China's mainland are included for the period between 2000 and 2016, constituting a panel dataset.

The data source and management of the dependent variable

To calculate the dependent variable, TFEE, the super-efficiency SBM model was applied. Unlike the calculation of single energy efficiency, we should define the input variables as well as the output variables at first in the super SBM model. Similar to previous literature regarding calculating TFEE, energy, capital stock, and labor are recognized as input variables. Real GDP is defined as the desired variable, and SO_2 is defined as the undesired variable. For the input factors, data on the energy is available from *China's Energy Statistical Yearbook*. The number of employees in China's three industries is applied to denote the labor inputs and is sourced from *China's Statistical Yearbook*. Another input factor, capital stock, is calculated through the perpetual inventory method, shown as:

$$K_t = (1 - \sigma) \bullet K_{t-1} + I_t \tag{13}$$

where t represents the period of time. I denotes the fixed-asset investment, which has been converted to constant price in 2000 through the price index of the fixed asset investment. σ stands for the depreciation rate and was assigned to be 9.6%. The corresponding data on fixed-asset investment and price index of the fixed asset investment are obtained from *China's Statistical Yearbook*. In addition, the capital stock for the base year (2000) can be obtained through:

$$K_{2000} = \frac{I_{2000}}{g_{2000-2016} + \sigma} \tag{14}$$

where $g_{2000-2016} = \left[\frac{I_{2016}}{I_{2000}}\right]^{1/16}$ stands for the average annual growth rate of fixed-asset investment between 2000 and 2016. The corresponding data of SO_2 emissions are sourced from *China Statistical Yearbook*.

Data source and management of other variables

The energy-saving patents are applied to denote the technological progress of the energy field and are sourced from China's State Intellectual Property Office. The two popular methods to obtain this information include searching the keywords or the corresponding International Patent Classification (IPC) codes. By referring to Wang et al. (2012) and Li and Lin (2016), we first identified the energy-conservation patents by reading detailed descriptions of the patent codes and aggregating the number of energy-conservation patents that belong to the IPC codes. Then, based on the date of the patent application, the number of energy patents from different sources was obtained by searching relevant keywords: research institutions, universities/colleges, and businesses from the applicant column.[3] The additional conditions with

[3] Since the research institutions and university/colleges share a lot of common points such as research grant sources and belong to the public, we assumed them as a whole. Other sources of energy technology refer to energy technology that does not belong to the research institutions, university/colleges, or businesses.

Table 1 Variable definitions

Variables	Definitions	Data sources
ln*TFEE*	Log form of total factor of energy efficiency	China Energy Statistical Yearbook; China Statistical Yearbook
ln*SPAT*	Log form of the stock of the total energy patents	China's State Intellectual Property Office
ln*BPAT*	Log form of the stock of the energy patents from business	China's State Intellectual Property Office
ln*IPAT*	Log form of the stock of the energy patents from independent research institutions	China's State Intellectual Property Office
ln*OPAT*	Log form of the stock of the energy patents from other organizations	China's State Intellectual Property Office
ln*UPAT*	Log form of the stock of the utility-type of energy patents	China's State Intellectual Property Office
ln*CPAT*	Log form of the stock of the creation-type of energy patents	China's State Intellectual Property Office
ln*FDI*	Log form of the share of FDI in actual use to the fixed-asset investments	China Statistical Yearbook
ln*TLL*	Log form of the Theil index	China Statistical Yearbook
ln*EP*	Log form of the purchasing price index for fuels and power,	China Statistical Yearbook
ln*SOE*	Log form of the ratio of output represented by state-owned industrial enterprises above a designated size to the output of all industrial enterprises above a designated size	China's Statistical Yearbook
Policy	Dummy variable (year before 2005 = 0, others 1)	

the provincial names can be applied to determine the number of energy patents in different provinces.

To calculate the degree of the industrial structure optimization through Model (9), the data on the GDP and employment of China's primary, secondary, and tertiary industries were employed. These data can be found in *China Statistical Yearbook*. In addition, considering that there are no official data available on energy prices, the purchasing price index for fuels and power is applied as the proxy for energy price, sourced from *China Statistical Yearbook*. FDI is denoted by the share of FDI in actual use to the fixed-asset investments, which is sourced from *China Statistical Yearbook*. Lastly, in line with Huang et al. (2019), the ratio of output represented by state-owned industrial enterprises above a designated size to the output of all industrial enterprises above a designated size[4] (hereafter the share of SOEs) is introduced as a proxy variable to reflect the effect of economic reform on TFEE. The corresponding data can be found in *China's Industry Statistical Yearbook*. Tables 1 and 2 show the definitions and descriptions of the aforementioned variables in the regression model, respectively.

Results and discussions

Unit root test

Since the cointegration analysis is able to avoid the spurious regression problem, it is frequently conducted before carrying out the empirical analysis. However, all the variables of order n ($n = 0, 1, 2, \ldots, N$) are to be integrated as a precondition for the cointegration analysis. As a result, the Levin–Lin-Chu method (Levin et al. 2002) is applied at first. The corresponding estimates are shown in Table 3. As shown, the test results for the original levels of all variables are statistically significant, with the p-values of < 0.05, indicating that all these variables are stationary.

Results and discussions from the conventional analysis

When the lagged term of the dependent variable is introduced in our empirical model, another cause for the endogenous problem, the conventional models, such as fixed effects (FE) and random effects, may be biased. To account for this, the generalized method of moments (GMM) approach, which is able to obtain consistent estimation results, was applied. There are two common strands of the GMM estimator: the difference GMM (DIFF-GMM) and the system GMM (SYS-GMM). As the SYS-GMM is able to address the weak independent variables, we applied the SYS-GMM estimator for our estimation. Table 4 shows the corresponding estimates based on the SYS-GMM estimators in which FDI is treated as the endogenous variable because of the causal nexus between FDI and TFEE.

The first column of Table 4 reports the estimates of the whole effect of energy technology on TFEE. The second column of this table shows the estimates by dividing the energy technology according to its sources. The third column presents the estimates by classifying the energy technology according to its purposes: utility model and creation type.

Energy technology is able to reduce the amount of the input factors when producing the same output, and therefore,

[4] [6] We must note that in China, before 2011, an enterprise above a designated size means that the output of this enterprise is more than 5 million Yuan RMB in the current year.

Table 2 Correlations of the variables

	ln*TFEE*	ln*SPAT*	ln*BPAT*	ln*IPAT*	ln*OPAT*	ln*UPAT*	ln*CPAT*	ln*FDI*	ln*TLL*	ln*EP*	ln*SOE*	*Policy*
ln*TFEE*	1											
ln*SPAT*	0.0057	1										
ln*BPAT*	-0.0434	0.9566	1									
ln*IPAT*	-0.0221	0.9177	0.9202	1								
ln*OPAT*	0.0240	0.9632	0.8729	0.8451	1							
ln*UPAT*	0.0270	0.9889	0.9624	0.9119	0.9498	1						
ln*CPAT*	-0.0508	0.9803	0.9343	0.9111	0.9366	0.9523	1					
ln*FDI*	0.5062	0.2223	0.1669	0.1760	0.2884	0.2415	0.1745	1				
ln*TLL*	-0.4320	-0.5121	-0.5021	-0.4542	-0.4765	-0.5135	-0.4899	-0.6022	1			
ln*EP*	0.3510	-0.5832	-0.6636	-0.5742	-0.4748	-0.5716	-0.5961	0.2374	0.2027	1		
ln*SOE*	0.0487	-0.5728	-0.5998	-0.4810	-0.5903	-0.5998	-0..5323	-0.3384	0.4309	0.3161	1	
Policy	-0.3898	0.4984	0.5760	0.5413	0.3933	0.4727	0.5476	-0.2218	-0.1243	-0.7819	-0.3590	1

Table 3 The unit root test based on LLC approach[a]

Variables	Level	
	Statistic-value	*p*-value
ln*TFEE*	− 1.8274**[b]	0.0338
ln*SPAT*	− 3.3596***	0.0004
ln*BPRT*	− 4.7595***	0.0000
ln*IPAT*	− 6.1705***	0.0000
ln*OPAT*	− 3.0456***	0.0000
ln*UPAT*	− 5.6317***	0.0000
ln*CPAT*	− 5.2877***	0.0000
ln*FDI*	− 2.0534**	0.0200
ln*TLL*	− 5.5643***	0.0000
ln*SOE*	− 6.4947***	0.0000
ln*PRICE*	− 2.2208**	0.0132

[a]LLC denotes the Levin, Lin, and Chu *t* test and the LLC tests for all the series include the constant and time trend. As suggested by Levin et al. (2002), we first subtract the cross-sectional averages from the series to mitigate the impact of cross-sectional dependence. We then set two lags of the series in the ADF regressions and use the Bartlett kernel with a maximum lag determined by the Akaike information criterion. [b]*** and **denote significance at the 1% level and the 5% level, respectively

TFEE is expected to improve. However, as businesses are at the forefront of production, they have a privilege of understanding the practical problems regarding poor energy efficiency. Additionally, since the funds for carrying energy R&D are mainly funded by the businesses themselves, they have strong motivations for pursuing maximum profits. Compared to businesses, both research institutions and other sources of energy technology are removed from the production line and have difficulty finding the causes of a low degree of TFEE. As a result, when considering the heterogeneity of energy technology from the perspective of its source, we found that only the technology coming from businesses can significantly improve TFEE, while the technology coming from research institutions (including universities/colleges) and others cannot effectively promote TFEE. This finding indicates that the positive promotion role of energy conversation technology in TFEE is mainly from businesses rather than independent research institutions and others. Furthermore, when heterogeneity is considered from the perspective of purpose, even though the utility-type of energy technology possesses less technical contents compared to the creation-type, as shown in the third column of Table 4, we found that only the utility-type of energy technology is able to increase TFEE with significance while the creation-type cannot. There are particular reasons responsible for this result: First, the utility-type of energy technology is mainly devoted to solving practical production issues while the creation-type aims to possess more scientific value. Second, its practicability also helps the utility-type of energy technology gain more popularity than the creation-type of energy technology.

For other driving factors, the relationship between FDI and TFEE may be complicated because of its relationship with economic and social environments such as the technological absorptive capacity. As shown in previous literature, the relationship between FDI and environmental performance, regarding single energy efficiency and TFEE, is not clear. In our study, similar to Huang et al. (2021), we have not captured the solid significant evidence that FDI is beneficial for TFEE. A higher degree of economic structure optimization indicates that input resources are allocated more reasonably, ensuring a higher level of TFEE. As indicated in Table 4, the coefficient of the economic structure optimization, denoted by the Theil index (i.e., ln*TLL*), is negative and significant, showing that economic structure optimization is able to improve TFEE. In addition, the evolution of the energy price will exert important effects on the amount of inputs because there is a substitution relationship among different factors. As the rise in the price of energy will increase the cost for energy consumers, it follows that consumers will feel motivated to enhance their consciousness of saving energy and promoting technological innovation; therefore, the efficiency of energy use may increase

Table 4 Results from the system GMM estimator

No Variables	1 SYS-GMM	2 SYS-GMM	3 SYS-GMM
Constant	0.0235 (0.0482)	0.0977* (0.0594)	0.0491* (0.0277)
*L.*ln*TFEE*	0.9346***[a] (0.0454)[b]	0.9397*** (0.0472)	0.9275*** (0.0299)
ln*SPAT*	0.0255*** (0.0075)		
ln*BPAT*		0.0132** (0.0065)	
ln*IPAT*		0.0009 (0.0042)	
ln*OPAT*		−0.0070 (0.0048)	
ln*UPAT*			0.0168*** (0.0063)
ln*CPAT*			0.0083 (0.0063)
ln*FDI*	0.0029 (0.0092)	−0.0041 (0.0059)	0.0025 (0.0053)
ln*TLL*	−0.0223* (0.0121)	−0.0370* (0.0200)	−0.0239*** (0.0067)
ln*PRICE*	0.0900*** (0.0264)	0.0778*** (0.0242)	0.0944*** (0.0108)
ln*SOE*	0.0421* (0.0241)	0.0128 (0.0111)	0.0436*** (0.0129)
Policy	0.0269*** (0.0083)	0.0778*** (0.0242)	0.0274*** (0.0025)
AR(1)	−1.98**	−2.00**	−2.04**
AR(2)	−0.77	−0.90	−0.79
Hansen	26.20	24.75	26.67
Hausman	83.89***	68.50***	86.43***
Wald	2469.98***	2495.03***	2812.58
Observations	480	480	480

(a) ***, **, and * denote the significance at the 1%, 5%, and 10% level. (b) Values in () denote the robust std. error for the coefficient. In the SYS-GMM estimators, the first-order of TFEE (i.e., *L.*ln*TFEE*) and the second and above terms of the endogenous variable (i.e., ln*FDI*) are selected as the independent variables

accordingly. The coefficients on the energy price are estimated to be positive and significant, suggesting China's increase in energy price will significantly drive TFEE. Considering that state-owned businesses are more poorly managed compared to non-state-owned ones, the reform characterized by the shift from being a state-owned business to a non-state-owned business, such as the joint venture enterprise, is quite beneficial in promoting TFEE. Lastly, the energy efficiency improvement policy initiated in 2005 is presented as an effective way to enhance TFEE.

Robustness check

To check the robustness of our estimates, FDI was replaced by another openness variable-trade, which is defined as the ratio of export and import to GDP. The corresponding regressions are shown in Table 5. By comparison, the estimates are almost identical as shown in the preceding table (Table 4), suggesting that our regressions are robust.

Results and discussions from the dynamic spatial Durbin model

As there may exist strong spatial correlations among China's regions, to further explore how the energy technologies affect TFEE, the dynamic spatial model is applied.

Spatial correlation test

Before examining the spatial dynamic impact of technological progress on TFEE, it is necessary to analyze whether there is a spatial correlation of TFEE among Chinese provinces. The global Moran's I index is generally used to measure spatial correlation. The global Moran's I statistics of China's TFEE is constructed as follows:

$$Moran'sI = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}[TFEE_i - \overline{TFEE}][TFEE_j - \overline{TFEE}]}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{15}$$

where $S^2 = \frac{\sum_{i=1}^{n}(TFEE_i - \overline{TFEE})^2}{n}$ is the sample variance of TFEE; w_{ij} represents the spatial weight matrix, which is used to measure the distance between region i and region j, and $\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$ stands for the sum of all spatial weights.

Moran's I is generally between −1 and 1. If the value of Moran's I statistic is more than 0 and significant, it indicates that the TFEE of a province is positively correlated with that of its neighboring provinces; if the Moran's I statistic is less than 0 and significant, it indicates that the TFEE of a province is negatively correlated with that of its neighboring provinces; finally, if the Moran's I statistic is

Table 5 The robustness test

No Variables	1 SYS-GMM	2 SYS-GMM	3 SYS-GMM
Constant	−0.0112 (0.0996)	0.0894 (0.0821)	0.0262 (0.0874)
L.ln*TFEE*	0.8903***[a] (0.0464)[b]	0.9019*** (0.0523)	0.9128*** (0.0433)
ln*SPAT*	0.0168** (0.0076)		
ln*BPAT*		0.0067* (0.0038)	
ln*IPAT*		0.0031 (0.0034)	
ln*OPAT*		−0.0059 (0.0039)	
ln*UPAT*			0.0169** (0.0079)
ln*CPAT*			0.0073 (0.0056)
ln*Trade*	0.0273 (0.0183)	−0.0065 (0.0108)	0.0087 (0.0124)
ln*TLL*	−0.0311** (0.0156)	−0.0373* (0.0197)	−0.0304* (0.0190)
ln*PRICE*	0.0646*** (0.0064)	0.0590*** (0.0223)	0.0466** (0.0190)
ln*SOE*	0.0431** (0.0268)	0.0127 (0.0140)	0.0248* (0.0137)
Policy	0.0249*** (0.0071)	0.0221*** (0.0061)	0.0290*** (0.0058)
AR(1)	−2.17**	−1.99**	−2.11**
AR(2)	−0.62	−0.92	−0.76
Hansen	27.16	25.73	27.80
Hausman	83.12***	71.84***	91.04***
Wald	591.31***	1807.39***	2033.21***
Observations	480	480	480

(a) ***, **, and * denote the significance at the 1%, 5%, and 10% level. (b) Values in () denote the robust std. error for the coefficient

0 or not significant, it indicates that the spatial distribution of the TFEE among provinces is random and there is no spatial correlation.

Table 6 shows the global Moran's *I* statistical results of China's TFEE from 2000 to 2016. According to the data in Table 6, during the period from 2000 to 2016, all global Moran's *I* values are positive and significant at the level of 10%, indicating that there is a spatial positive correlation of TFEE among the provinces of China.

Results and discussion

Table 7 shows the estimated results based on DSDM. The table includes the estimation results of three DSDMs. The second column of Table 7 shows the effect of total energy technology on China's TFEE. The third column of Table 7 presents the effect of energy technology from different sources on China's TFEE. Finally, the last column shows the effect of energy technology with different purposes on China's TFEE. In these three DSDMs, the variance expansion coefficients are less than 10, indicating that there is no collinearity problem in these three models. The results of the Hausman test are significant at the 1% level, which indicates that the FE is more appropriate. The results of the Wald test are also significant at the 1% level, suggesting that DSDM is more suitable for our estimation than SLM and SEM. In addition, the estimated coefficients on the lag term (*L*.ln*TFEE*) and spatial term (*L*.*W** ln*TFEE*) of TFEE are significant at the 1% level, confirming that DSDM is more suitable for our estimation.

Based on these estimates, we can calculate the direct, indirect, and whole effects of energy technology on TFEE. Table 8 lists the estimated results of long-term energy technology on China's TFEE. As shown, similar to the conventional analysis, the estimated coefficient concerning the total effect of energy technology on TFEE is significant, indicating that energy technology can effectively drive the growth of TFEE. However, this positive TFEE

Table 6 The global *Moran's I* statistic and its *p*-value of China's TFEE between 2000 and 2016

Year	*Moran's I*	*p*-value	*Year*	*Moran's I*	*p*-value
2000	0.101	0.071	2009	0.164	0.051
2001	0.113	0.082	2010	0.170	0.045
2002	0.121	0.083	2011	0.171	0.043
2003	0.134	0.072	2012	0.161	0.042
2004	0.141	0.070	2013	0.178	0.035
2005	0.138	0.065	2014	0.181	0.034
2006	0.148	0.061	2015	0.186	0.022
2007	0.152	0.053	2016	0.191	0.020
2008	0.160	0.050			

(1) The results are based on the stata command "spatgsa." (2) "average" is the *Moran*'s *I* statistic estimated with provinces' average total factor of energy efficiency between 2000 and 2016

Table 7 The estimation results based on SDDM

No	1	2	3
Variables	SDDM	SDDM	SDDM
*L.*ln*TFEE*	0.9799***[a]	0.9940***	0.9919***
	(0.0467)[b]	(0.0455)	(0.0469)
*L.W**ln*TFEE*	−0.3327***	−0.3455***	−0.3365***
	(0.070)	(0.0704)	(0.0754)
*W**ln*TFEE*	0.3076***	0.3296***	0.2566***
	(0.0537)	(0.0483)	(0.0553)
ln*SPAT*	−0.0126**		
	(0.0060)		
ln*BPAT*		−0.0197*** (0.0049)	
ln*IPAT*		−0.0058 (0.0043)	
ln*OPAT*		0.0081 (0.0081)	
ln*UPAT*			0.0178**
			(0.0077)
ln*CPAT*			−0.0039
			0.0039
			(0.0250)
ln*FDI*	0.0114**(0.0053)	0.0093*(0.0051)	0.0098*(0.0052)
ln*TLL*	0.0260***	0.0252***	0.0243***
	(0.0084)	(0.0075)	(0.0077)
ln*PRICE*	0.0295	0.0381**	0.0276
	(0.0206)	(0.0187)	(0.0221)
ln*SOE*	−0.0228	−0.0309	0.0197
	(0.0359)	(0.0337)	(0.0352)
Policy	0.0015	−0.0013	−0.0015
	(0.0014)	(0.0017)	(0.0032)
W×ln*SPAT*	0.0013		
	(0.0079)		
W×ln*BPAT*		−0.0024	
		(0.0084)	
W×ln*IPAT*		0.0058	
		(0.0059)	
W×ln*OPAT*		−0.0029	
		(0.0120)	
W×ln*UPAT*			0.0157
			(0.0130)
W×ln*CPAT*			−0.0148**
			(0.0070)
W×ln*FDI*	0.0157*	0.0104	0.0122
	(0.0087)	(0.0095)	(0.0088)
W×ln*TLL*	−0.0664***	−0.0593**	−0.0749***
	(0.0241)	(0.0251)	(0.0232)
W×ln*PRICE*	0.0096 (0.0249)	−0.0034 (0.0265)	0.0082 (0.0259)
W×ln*SOE*	0.0017(0.0332)	0.0166(0.0315)	0.0128(0.0323)
W×*Policy*	0.0092 (0.0060)	0.0083 (0.0063)	0.0148** (0.0063)
σ^2	0.0008***	0.0008***	0.0008***
	(0.000)	(0.000)	(0.000)
VIF	9.04	9.28	8.31
*Wald*1(*p*)	17.25***	19.29***	16.08***

Table 7 (continued)

No	1	2	3
*Wald*2(*p*)	23.74***	22.74***	20.16***
LL	981.607	984.609	994.457
Within-R^2	0.9298	0.939	0.9520
Observations	480	480	480

(a) ***, **, and * denote the significance at the 1%, 5%, and 10% level. (b) Values in () denote the std. error for the coefficient. *L.*ln*TFEE* stands for the first-order lag of dependent variable (i.e., ln*TFEE*). (c) *W* is the spatial weight matrix. $W \times X$ stands for the product of *W* and the variable *X,* representing the spillover effect of the variable *X* on TFEE. (d) *Wald* test is applied to determine whether SDAR, SDEM, or SDDM would be fit for our estimations. *Hausman* test is used to choose between the fixed effect model and the random effect model. *VIF* is used to determine whether, or not, the multiple mutual linear problem exists

Table 8 The direct, spatial, and total effects of energy technology on TFEE

No	1			2			3		
Variables	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ln*SPAT*	0.0135**[a]	0.0070	0.0204**						
	(0.0055)[b]	(0.0095)	(0.0101)						
ln*BPAT*				0.0205***	0.0057	0.0263*			
				(0.0049)	(0.0127)	(0.0148)			
ln*IAT*				−0.0063	0.0108	−0.0172			
				(0.0042)	(0.0092)	(0.0190)			
ln*OPAT*				0.0076	−0.0022	0.0053			
				(0.0083)	(0.0178)	(0.0225)			
ln*CPAT*							−0.0045**	−0.0198**	−0.0243**
							(0.0037)	(0.0089)	(0.0099)
ln*UPAT*							0.0187**	0.0244*	−0.0432**
							(0.0073)	(0.0157)	(0.0169)
ln*FDI*	0.0132**	0.0269**	0.0401**	0.0103*	0.0175	0.0279*	0.0110**	0.0186*	0.0296*
	(0.0057)	(0.0135)	(0.0177)	(0.0054)	(0.0141)	(0.0180)	(0.0054)	(0.0114)	(0.0151)
ln*TLL*	0.0212***	−0.0793**	−0.0581*	0.0207**	−0.0735**	−0.0527*	0.0199***	−0.0922***	−0.0722**
	(0.0077)	(0.0305)	(0.0302)	(0.0068)	(0.0327)	(0.0322)	(0.0071)	(0.0298)	(0.0289)
ln*SOE*	−0.0243	−0.0048	0.0290	−0.0309	0.0096	0.0213	−0.0197	0.0106	0.0090
	(0.0358)	(0.0343)	(0.0387)	(0.0318)	(0.0348)	(0.0350)	(0.0330)	(0.0350)	(0.0361)
ln*PRICE*	0.0310	0.0221	0.0532*	0.0394**	0.0127	0.0521*	0.0281	0.0172	0.0353
	(0.0196)	(0.0290)	(0.0330)	(0.0178)	(0.0324)	(0.0307)	(0.0216)	(0.0308)	(0.0342)
POLICY	−0.0008*	0.0112	0.0103	−0.0007	0.0106	0.0099	0.0022	0.0192	0.0215
	(0.0005)	(0.0080)	(0.0084)	(0.0006)	(0.0088)	(0.0090)	(0.0316)	(0.0133)	(0.0430)

(a) ***, **, and * denote the significance at the 1%, 5%, and 10% level. (b) Values in () denote the std. error for the coefficient

promotion effect is mainly from the direct channel because only the estimated coefficient on the direct effect is positive and significant. After dividing the energy technology into different sources and purposes, we still found that only the coefficients on the technology from businesses are significant, suggesting that the TFEE promotion effect is mainly accredited to business energy technology. We also find that the positive TFEE promotion effect is from direct, rather the indirect, channels. When further considering energy technology's influence on TFEE from the perspective of its purpose, the utility-type, rather than the creation-type of energy technology, is found to drive TFEE with significance, with the indirect channel having a more important role than the direct channel. On the contrary, the creation-type of energy technology even impedes the promotion of TFEE.

Since attracting FDI and achieving industrial structure optimization are two of the governments' major targets, when a region has fulfilled these targets, it will conduct pressure on its neighboring regions, and the neighboring regions will try their best to improve their targets. As the estimates show, both the openness through FDI and industrial structure optimization are found to drive TFEE with significance, and their positive promotion effects are mainly from the indirect channel. Regarding energy price, similar to the conventional analysis, the total effect of increasing the energy price is found to drive TFEE with significance.

Conclusions and policy implications

Based on a panel data of China's 30 regions in the period of 2000–2016, this paper analyses the impact of technological progress in the energy field (i.e., energy patents) on TFEE. The following conclusions and policy implications can be summarized according to the empirical analysis with both conventional and spatial econometrics.

Conclusions

From the whole analysis, the energy technology, together with the industrial structure optimization and regulation of energy price, significantly contributes to the evolution of the total factor of energy efficiency. It is notable that the China's TFEE can be significantly improved by energy technology. However, when considering heterogeneity in the energy technologies from the perspective of their sources and purposes, we find that not all kinds of energy technologies are able to improve TFEE; only business energy technology is effective in enhancing TFEE. Compared to the creation-type of energy technology, the utility-type is more effective in improving TFEE. When we further explored how energy technology influences TFEE by considering spatial correlation, it was found that the energy technology in one region will not exert effects on its regional TFEE but will have important effects on the TFEE of its neighboring regions.

Second, apart from the energy technology innovation, both the continuous optimization in the industrial structure and regulation of energy price contribute to the increase of TFEE. From the sources of the positive role the industrial structure optimization played in TFEE, the spillover effects from the neighboring regions are more important compared to the industrial structure optimization of the region itself.

Policy implications

The above conclusions can help us present the following policy implications. Among the different factors of TFEE, the energy technology, together with the continuous optimization of the industrial structure and the market-oriented reform of energy prices, is important to TFEE and should be attached with special attentions. First of all, it is no doubt that the energy technology innovation is of great importance to improving the TFEE. However, when looking into the heterogeneity that exists in energy technology, the creation-type of energy technology from the businness has a more important role in enhancing the TFEE compared to other kinds of technology. According to these findings, more particular and targeted energy policies related to encouraging businesses to perform more R&D would be more effective in enhancing TFEE. Additionally, as creating energy technology is a difficult process with a high level of uncertainty, the energy policies that make full use of this spatial effect to further enhance TFEE can be popular alternatives.

Second, apart from the energy technology, the continuous optimization in the industrial structure is also important to TFEE. This hints that the current readjustment of industrial structure shifting from agriculture to industry and finally to tertiary industry is able to facilitate the resource turnover, and the governments should confirmedly promote the upgrading of the industrial structure.

Lastly, considering that there is a substitution effect among different input factors when producing the output, price is one of the key factors determining the ratio of different input factors and is therefore important to TFEE. The regulation of energy price may be demonstrated as an important component in decreasing the energy inputs. Therefore, by continuously strengthening market-oriented reform related to energy prices and regulating the energy prices, a suitable reform orientation for China can be achieved in the long term.

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