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Spatial econometric analysis of factors influencing regional energy efficiency in China

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Abstract
Increased environmental pollution and energy consumption caused by the country's rapid development has raised considerable public concern, and has become the focus of the government and public. This study employs the super-efficiency slack-based model–data envelopment analysis (SBM–DEA) to measure the total factor energy efficiency of 30 provinces in China. The estimation model for the spatial interaction intensity of regional total factor energy efficiency is based on Wilson's maximum entropy model. The model is used to analyze the factors that affect the potential value of total factor energy efficiency using spatial dynamic panel data for 30 provinces during 2000–2014. The study found that there are differences and spatial correlations of energy efficiency among provinces and regions in China. The energy efficiency in the eastern, central, and western regions fluctuated significantly, and was mainly because of significant energy efficiency impacts on influences of industrial structure, energy intensity, and technological progress. This research is of great significance to China's energy efficiency and regional coordinated development.

Keywords Energy efficiency · Sustainability · Emerging economies · Spatial interaction · Spatial dynamic panel

Introduction

To promote energy revolution, reform energy production, and utilization modes, and improve the energy utilization rate, China proposed to build a clean, low-carbon, safe, and highly effective modern energy system that focuses on the adjustment of the energy structure, construction of modern energy storage, and transportation networks, and an intelligent energy system in its Thirteenth Five-Year Plan. However, given the actual conditions within its vast territory, economic development and energy efficiency remain unbalanced across various provinces, and thus, it is essential to consider regional discrepancy when formulating energy conservation policies (Bian et al. 2017). To this effect, analyzing the effects of factors, spatial conditions, and the dynamic distribution of discrepancies among various provinces on energy efficiency can help reduce the energy

efficiency gap, and accomplish the task of building a new modern energy system under the Thirteenth Five-Year Plan.

Since its accession to the WTO in 2001, China opened itself up to foreign investments. By 2014, it became the top destination for FDI, reaching an amount of US$1.28 trillion. However, at the same time, the country was faced with the disadvantages of a fast-growing economy, including increased consumption of resources and environmental deterioration; lowering of environmental regulations by local governments to attract pollutive enterprises; market segmentation derived from an officer promotion mechanism; and restricted flow of labor force, capital, and energy elements into markets. There is growing public demand for environment protection given the increasing pollution levels because of energy consumption, strength, and efficiency problems. Despite this, research on the effects of factor flow at the regional spatial level to other provinces remains rare.

The following research work is carried out in this paper. First, by adopting the super-efficiency slack-based model–data envelopment analysis (SBM–DEA) method (Tone 2002) that accounts for output, this study estimates the total factor energy efficiency of every Chinese province. Second, considering geographical spatial interactions, a measuring model for the spatial interaction strength of total factor energy efficiency is constructed. Third, against a possible spatial autocorrelation,

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the space Durbin model is used to quantitatively analyze the effects of industrial structure, governmental interference, and energy strength on the spatial interaction strength of energy efficiency. Third, based on spatial correlation, the factors of influence of industrial structure, government intervention, and energy intensity on spatial interaction of energy efficiency are analyzed. The main innovation of this paper is to construct a spatial dynamic model based on Wilson's maximum entropy model to analyze the direct and indirect effects on the factors that affect energy efficiency.

Literature reviews

Following a century of development, there are three main types of energy efficiency definitions—energy production efficiency, energy strength, and total factor energy efficiency. Energy production efficiency is expressed by the ratio of gross domestic product (GDP) to one input factor derived from the productivity of a single factor in a department's production function. Energy productivity is a single-factor productivity, which is usually expressed as a ratio of output (usually GDP) to an energy input factor. Energy strength is generally used to reflect the level of energy utilization efficiency; it is expressed by the ratio of energy input to output. However, these two definitions do not account for other input factors related to production. In fact, total factor energy efficiency considers not only energy input factors, but also other relevant factors. Hu and Wang (2006) proposed an estimation method for total energy efficiency that obtains maximum output under a restricted input factor level, and relatively sequences energy efficiency by comparing distances from the samples to the production frontier.

As for China's regional energy efficiency, scholars have conducted extensive research, and derived conclusions with practical significance. They have studied energy efficiency and intensity improvements to explore the relationship between energy and economy (Alam et al. 2015). Schleich et al. (2009) stated that the EU emissions trading scheme could improve energy efficiency and reduce carbon emission through environmental regulations, such as restrictions on energy price. Many scholars highlight the close relationship between improved economic development and energy efficiency and strength (Hang and Tu 2007; Stern 2015). Technical efficiency in the industrial sector (Wang et al. 2012), technological progress, governmental intervention, and change in energy consumption structure (Lv et al. 2015; Yuxiang and Chen 2010; Ai et al. 2015) have a certain impact on energy efficiency changes.

Research on factors that influence regional energy efficiency with consideration for spatial interactions dates back to as early as the end of the nineteenth century. For instance, Ravenstein (1976) examined population migration on the basis of spatial feature rules. In the article *Commodity Circulation in America*, geographer Ullman (1957) explored spatial interactions using

multidisciplinary theory models by referring to Ohlin (1934) and Stouffer (1940). In the context of China, some scholars demonstrated the spatial effect or dependency in provincial energy efficiency (Guan and Xu 2016; Ying-Zhi and Guan 2011). Lv et al. (2017) showed a significant spatial spillover effect in the east and west regions of China, suggesting that spatial factors should be introduced in research on variations in energy efficiency.

While numerous achievements have been made in research on China's energy efficiency and factors that influence it, studies that consider spatial interaction strength and employ a spatial econometric model to analyze regional energy efficiency and influencing factors still have scope for improvement (Cheng et al. 2013; Guan and Xu 2016; Wang et al. 2014). Moreover, considering rapid information exchanges among provinces, and how such communication could result in a spatial spillover effect, energy efficiency studies that measure the strength of spatial interactions among provinces and influencing factors remain insufficient.

In recent years, scholars have also considered reducing carbon emissions in order to improve eco-efficiency from the perspective of the industry's overall supply chain and region (Gunasekaran 2014; Gul et al. 2015; Govindan and Sivakumar 2016; Carvalho et al. 2017). Considering industrial agglomeration analysis, some scholars researched industrial energy efficiency from the perspective of a space Markov chain test of China's energy efficiency convergence and the "club effect" (Costantini et al. 2017; Pan et al. 2015), and others focused on regional research, usually conducted by regions east, west, and center (Song et al. 2017; Chen et al. 2016; Lv et al. 2017), or traditionally, six major geographical locations, in order to explore variations in energy efficiency and its relationship with economic growth. Li and Wu (2016) divided regions on the basis of their political attributes.

The data envelopment analysis (DEA) model becomes an important technical means in energy efficiency research. It is based on a nonlinear mathematical programming method, different from the econometrics method. Rojas-Cardenas et al. (2017) compared and analyzed the difference in energy intensity between the graphite industry in Mexico and that in China and the USA. Lin and Liu (2017) analyzed the energy efficiency of China's transportation sector using DEA, and truncated regression and its influencing factors. All of the explorations mentioned above have broadened the academic scope for other scholars.

Model

Estimation method for energy efficiency

DEA is a nonparametric method derived through solving a linear programming problem. It is widely used because it does not require many forms of data and production frontiers, evaluates every decision-making unit (DMU), and compares input

and output factors. Other methods that evaluate total factor energy efficiency include the stochastic frontier analysis (SFA) and Solow residual method (SRM). The accuracy of total factor energy efficiency values is affected by that of the selection of a production function. The basic approach of a DEA is to estimate the nonparametric envelopment frontier of effective production to identify effective and ineffective points on the basis of whether these points are on the frontier line. Suppose there are *DMUs*; here, each province is treated as a DMU, and every province has K types of input factors to produce M output. The following linear programming is used to determine the efficiency value of the ith DMU:

$$\text{Min}_{\theta,\lambda} \sum \theta \ s.t. -y_i + Y\lambda \geq 0, \ \begin{matrix} \theta x_i - X\lambda \geq 0 \\ \lambda \geq 0 \end{matrix} \tag{1}$$

where constant vector λ is the $N \times 1$ order and scalar θ is the energy efficiency value. The evaluation rule is $\theta = 1$, indicating that the point is on the production frontier, and technically effective. $\theta \leq 1$ denotes that the ineffective point is not on the production frontier and generally under the frontier.

Although the traditional DEA models that are based on constant returns to scale (such as CCR model) and variable returns to scale (such as BCC model) consider multiple inputs and outputs, they generally ignore the problem of slack variables in the inefficiency calculation because they adopt a viewpoint that rests on radial distance function. The super-efficiency SBM–DEA, which is based on Tone (2001, 2002), resolves this problem by conducting an evaluation from a nonradial viewpoint; moreover, it addresses the undesirable output problem in which "bad output" in economic activities and the slack variable problem are avoided, and sequences multiple DMUs when they are all effective. An increasing number of scholars have adopted the SBM model for performance evaluation considering the environmental pollution resulting from economic production activities (Guo and Sun 2013; Qian and Liu 2013; Zhang et al. 2015; Zuo and Yang 2011):

$$\rho^* = \min \frac{1 - \frac{1}{N} \sum_{n=1}^{N} \frac{s_n^x}{x_{kn}^t}}{1 + \frac{1}{M+I} \left(\sum_{m=1}^{M} \frac{s_m^y}{y_{km}^t} + \sum_{i=1}^{L} \frac{s_i^b}{b_{kt}^t} \right)}$$

$$s.t. \begin{cases} \sum_{k=1,k \neq j}^{K} z_k^t x_{kn}^t + s_n^x = x_{kn}^t, n = 1, \cdots, N \\ \sum_{k=1,k \neq j}^{K} z_k^t x_{kn}^t - s_m^y = y_{km}^t, m = 1, \cdots, M \\ \sum_{k=1,k \neq j}^{K} z_k^t b_{kt}^t + s_t^b = b_{ki}^t, i = 1, \cdots, I \\ z_k^t \geq 0, s_n^x \geq 0, s_m^y \geq 0, s_i^b \geq 0, k = 1, \cdots, K \end{cases} \tag{2}$$

where $\left(x_{kn}^t, y_{kn}^t, b_{kn}^t \right)$ refers to input, desirable output, and undesirable output of a DMU at time t, and $\left(s_n^x, s_m^y, b_i^b \right)$ is their slack variable. This study uses the super-efficiency SBM–DEA

model to calculate the total factor energy efficiency of Chinese provinces.

Spatial interaction model for regional energy efficiency

Spatial interaction is defined as population mobility, commodity circulation, industrial transfer, capital inflow, and material and information exchange among different provinces and regions (Long et al. 2016). According to its form and connotation, spatial interaction is divided into three types—convection, radiation, and transmission. Improvements in regional energy efficiency not only depend on economic level, geographic location, and technical and institutional factors, but also involve population, commodity, industrial, and technical innovation.

Research on Ravenstein's gravity model finds that distance and spatial interaction are inseparable (Ravenstein 1976). Moreover, spatial interaction is related to regions' sizes, degree to which economic activities are related, and social development level. Combined with universal gravitation theory, the gravity model is used to calculate the strength of regional spatial interaction, that is, $I_{ij} = p_i p_j / D_{ij}^b$, where p_i and p_j denote size of region, D_{ij}^b is the distance between regions i and j, and b is the friction coefficient used to calculate distance. Accordingly, a potential model is developed to examine the strength of interaction among multiple regions, and obtain the summation of I_{ij}: $M = \sum_{j=1}^{n} I_{ij} = \sum p_i p_j / D_{ij}^b$; this process is called "potential." These two models have similar limitations—they lack rigorous mathematical formula derivation, the friction coefficient is not fixed, and its selection is subjective, all resulting in errors. Therefore, this study adopts Wilson's (1967) maximum entropy model to estimate the spatial interaction strength of energy efficiency for each province in China.

First, it assumes that the regional system is closed and satisfies the physics law of energy conservation. Then, when the entropy of the subsystem reaches maximum value, the macroscopic quantity will be stable, and the total system entropy will peak. In the long run, the instant flux will remain stable, and such a flux is called the strength of spatial interaction:

$$\sum_j T_{ij} = O_i \tag{3}$$

$$\sum_i T_{ij} = D_j \qquad i, j = 1, \cdots, n$$

$$\sum_{ij} c_{ij} T_{ij} = C$$

where T_{ij} is the strength of regional interaction. The total supply of region i is set to O_i, and the total demand of region j is D_j. Current cost is denoted by C. We obtain the extreme value using

$$W(T_{ij}) = \frac{T!}{\prod_{ij} T_{ij}!}. \tag{4}$$

This mode is set up by using probability, as well as permutation and combination knowledge, which is different from the aforementioned gravity and potential models.

Prasad (2005) attempted to measure regional interaction influence using a spatial interaction model. Some other scholars combined Wilson's model with commodity inflow and outflow in logistics theory to examine logistics spatial interaction. This study introduces a total factor energy efficiency index on the basis of a maximum entropy model. Regions with low energy efficiency often strive to bring in experiences, scientific technologies, and policy institutions of regions with high efficiency, in which case an appealing force tends to emerge. Thus, we put forward our first proposition.

Proposition 1 The appealing force between a supply region and a demand region denotes the total factor energy efficiency of each region.

Spatial damping factors, such as distance, communication, information, and degree of mutual exchange among different regions, also tend to differ. First, suppose 30 Chinese provinces are in a closed system. T_{ij} is used to express spatial interaction strength based on total factor energy efficiency when the macroscopic quantity is maximum. The model is constructed as follows:

$$\begin{aligned}
\sum_{i=1}^{n} T_{ij} &= E_{1i} & i = 1, \cdots n \\
\sum_{j=1}^{m} T_{ij} &= E_{2j} & j = 1, \cdots m, \\
\sum_{i=1}^{n} \sum_{j=1}^{m} c_{ij} T_{ij} &= C
\end{aligned} \tag{5}$$

where E_{1i} is the total supply of the ith region and E_{2j} is the total demand of the jth region. The entropy of the subsystem in thermodynamics is $S_j = -\sum_{i=1}^{N} \frac{T_{ij}}{E_{1i}} \log \frac{T_{ij}}{E_{1i}}$. The Lagrange function is used to obtain the extreme value of this formula, and when using the point of this extreme value, the subsystem's entropy and the macroscopic quantity of the closed system become stable. At this time, $T_{ij} = K_i E_{1i} \exp(-\beta c_{ij}) = K_j E_{2j} \exp(-\beta c_{ij})$, where β denotes the spatial damping function. Thus, we put forward our second proposition.

Proposition 2 When analyzing population diffusion and spatial interaction, the diffusion coefficient is $D = \frac{h^2}{2T}$ and $\beta = \sqrt{\frac{2T}{t_{max}D}}$. Here, h is the region diameter, and T is the residence time of persons in a given region.

The following equation is used to estimate spatial interaction strength for multiple regions while accounting for energy efficiency factors under the maximum entropy model:

$$T_i = \sum_{j=1}^{n} T_{ij} = E_{1i} E_{2j} \exp\left(-\sqrt{\frac{2T}{t_{max}D}} \gamma_{ij}\right) \quad (i \neq j), \tag{6}$$

where D is the administrative area of 30 provinces; T is the quantity of regions with interaction; t_{max} is the quantity of regions with high energy efficiency value; E_{1i} and E_{2j} are the energy efficiency values of a region with supply i, and a region with demand j; and T_i is the sum of spatial interactions among each province, and termed the potential value of total factor energy efficiency.

Spatial econometric model

Model introduction

The traditional econometric framework has been reformed with the development of spatial econometrics. In fact, the spatial spillover effect can be quantitatively analyzed on the basis of space, space and time, and geographical location considerations. In general, a data point in a spatial data sample expresses observed values related to regions, in which case the concept of "spatial dependence" is derived. This indicates that spatial correlation and time sequence correlation concurrently exist among regions.

Spatial autocorrelation analysis

When the values of variables for adjacent regions are similar, spatial autocorrelation may exist, which is also known as spatial dependence (Long et al. 2015). Introduced in 1950, Moran's index I is a commonly used method to test for spatial autocorrelation. This study employs Moran's index to explore the clustering effect of spatial interaction for each Chinese province, and then test the spatial correlation, the spatial interaction strength of the total factor energy efficiency for each province during 2000–2014. Stata 14.2 is used to calculate the value of Moran's I.

$$Moran's\,I = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \left(Y_i - \overline{Y}\right) \left(Y_j - \overline{Y}\right) / S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}, \tag{7}$$

where S^2 is the sample variance of an observed value (total factor energy efficiency value); Y_i, for the ith region; and $S^2 = \sum_{i=1}^{n} \left(Y_i - \overline{Y}\right) / n$, $\overline{Y} = \sum_{i=1}^{n} Y_i / n$. The value range for Moran's I is [-1, 1], where the negative value denotes a negative autocorrelation among regions, while a positive value refers to a positive autocorrelation. $I > 0$ means that high values are close

to high values, and low values are near low values, and $I < 0$ denotes that high values are next to low values. The geographical distance spatial weight matrix is the [0, 1] matrix under the adjacent criterion, and is standardized as follows:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_{i1} & w_{i2} & \cdots & w_{ij} \end{bmatrix}, \tag{8}$$

i, j refer to regions i, j. When the two regions are adjacent and have a common boundary, $w_{ij} = 1$, and when there is no common boundary, $w_{ij} = 0$. Finally, statistical magnitude Z is used to perform a significance test of Moran's I.

$$Z(d) = \frac{Moran's\ I - E(I)}{\sqrt{VAR(I)}}. \tag{9}$$

Spatial econometric analysis of factors influencing potential values of total factor energy efficiency

First, it is certain that a change in the potential value of total factor energy efficiency is caused by the combined action of multiple factors. Since it is difficult to list all influencing factors, drawing in the literature, this study focuses on industrial structure, FDI, transportation infrastructure, technical progress, and governmental intervention. To avoid multicollinearity and heteroscedasticity, this study takes the logarithm of each variable.

The spatial econometric model compensates for the deficiency in the traditional measurement model, that is, the latter does not account for spatial correlation, and includes a spatial function for each region. When setting up the model and analyzing the spatial effect, if the explained variable T_i for province i is related to every explanatory variable of the province and independent variables for adjacent provinces, then

$$T = X\beta + WX\delta + \varepsilon, \tag{10}$$

where $WX\delta$ is the influence of an independent variable for an adjacent province; δ is the influence coefficient; and T is the explained variable, the total factor energy efficiency potential value. When combined with a spatial autoregression model, we derive the space Durbin model:

$$T = \rho WT + X\beta + WX\delta + \varepsilon. \tag{11}$$

According to the above theoretical basis, we set up the dynamic panel space Durbin model

$$T_{it} = \tau T_{i,t-1} + \rho w_i T_{it} + X_{it}\beta + w_i X_{it}\delta + \mu_i + \gamma_t + \varepsilon_{it}, \tag{12}$$

where $T_{i,\ t-1}$ is the one-order lag for an explained variable, w_i is row i in spatial weight matrix W, the spatial lag term of the energy efficiency potential value is $w_i X_t \delta$, and the time effect is γ_t.

The study follows the spatial dependence model (SDM) to observe the spatial effect of an adjacent province (LeSage and Pace 2008):

$$\begin{aligned} T_{it} &= \frac{X_{it}\beta + w_i X_{it}\delta}{(I_n - \rho w_i)} + \frac{\mu_i + \gamma_t}{(I_n - \rho w_i)} + \frac{\varepsilon_{it}}{(I_n - \rho w_i)} \\ &= \sum_{k=1}^{5} H_k(w) X_{it} + L(w)(\mu_i + \gamma_t) + L(w)\varepsilon_{it} \\ H_k(w) &= L(w)(I_n\beta + w_i\delta) \\ L(w) &= (I_n - \rho w_i)^{-1} = I_n + \rho w_i + \rho^2 w_i^2 + \rho^3 w_i^3 + \cdots. \end{aligned} \tag{13}$$

Changes in an independent variable for one province will indirectly affect those in dependent variables for other provinces. $w_i T_{it}$ fits the difference in the potential values for total factor energy efficiency among provinces by capturing those for total factor energy efficiency of adjacent provinces, and given the independent variable feature level, $w_i X_{it}$. In other words, the spatial effect of each province is influenced by adjacent provinces. To measure the influence of change in an independent variable on T_{it}, the partial derivative of period t, which corresponds to the kth explained variable for one region at a certain period point, is solved:

$$\frac{\partial T_{it}}{\partial X_{it}} H_k(w)_{ij}. \tag{14}$$

Such an effect will simultaneously influence province i. The degree of reaction depends on the location of every province, the spatial weight matrix that reflects relationships among each province, and the spatial autocorrelation coefficient ρ and parameters μ_i, δ, γ_t. The elements on the diagonals of matrix $H_k(w)$ represent a direct effect, while those not on the diagonals and mean values denote an indirect effect. Pace and LeSage (2006) presented a measurement method by defining the mean value of the ith row of matrix $H_k(w)$ as the accepted average total effect of this region. A simple method to measure the average direct effect is to obtain the mean value of elements on the diagonal. In this case, the difference in subtracting the average direct effect from the average total effect will be the average indirect effect.

Average direct effect : (15)

$$\overline{M}(k)_{direct} = H_k(w)_{ii}/n = n^{-1} tk H_k(w).$$

Average total effect : (16)

$$\overline{M}(k)_{total} = H_k(w)_{ijsum}(\mu_i + \gamma_t)/n \qquad i \neq j.$$

Average indirect effect :   (17)

$$\overline{M}(k)_{indirect} = \overline{M}(k)_{total} - \overline{M}(k)_{direct}$$

In Eq. (16), *ijsum* is the row sum average value of elements that are not on the diagonals in matrix $H_k(w)$.

Empirical analysis

Data selection and variables

The Rawski (2001) study showed that, since the mid-1990s, China's economic growth trend and energy consumption growth trend have been in contrast with each other. Sinton and Fridley (2000), Sinton (2001) explored the relationship between China's economic growth, energy production, and actual output in this period, and stated that relevant statistical indicators were less credible. Thus, this study selects 2000 as the base year. Energy consumption data are released every other year, and relevant energy data are available till 2015 on the National Statistics Bureau's official website. Considering data availability and completeness, this study uses relevant energy data for 30 provinces for 2000–2014. The following regions are excluded owing to missing data: Tibet, Hong Kong, Macau, and Taiwan. Missing data are fixed using the mean value, ratio, and interpolation methods. Data for Tianjin city's transportation infrastructure are expressed in the total length of operational lines, as stated on the National Statistics Bureau's official website.

For data on GDP output, the gross regional domestic product for each province and a GDP deflator are used. Relevant data for the constant price of each year are obtained using 2000 as the base year. For the labor force index, it is preferable to employ average labor time and labor productivity for each region. However, considering data availability, this study uses the number of employees at the end of each year, data for which are taken from the relevant year's statistical yearbook for every province, which is half of the sum of last year's and current year's year-end employee number. For energy data, the total energy consumption for each province is chosen and converted into a unified unit, that is, 10,000 t of standard coal. Using relevant capital stock data updated to 2014, the perpetual inventory method is employed, that is, $K_{it} = K_{it-1}(1 - \delta_{it}) + I_{it}$, where K_{it} is the capital stock of the ith province in the tth year. Given space constraints, this study does not conduct a detailed estimation of the economic depreciation rate δ_{it}, but assumes it to be 9.6%, drawing on Zhang et al. (2004). As for the selection of data for investment I_{it}, the current system of national accounts provides a fixed asset price index and data on fixed asset investments for each province. The annual constant price for each fixed asset investment is calculated with 2000 as the base year. Accordingly, each year's capital stock is estimated by incorporating a fixed asset price

index in the formula. Undesirable output data include industrial solid waste emissions, industrial emissions, and industrial waste water discharge, and other major pollutant emission targets for each province during the last 15 years. Table 1 presents the statistical description indexes used to calculate energy efficiency from 2000 to 2014.

Geographically, 30 provinces are divided into three locations according to traditions, respectively, for the eastern, central, and western regions (Table 2).

In calculating the spatial interaction strength of regional total factor energy efficiency, $T = 30$ denotes the number of research objects, and t_{max} is the number of provinces whose mean value for the Malmquist–Luenberger (ML) index is greater than 1. The adjacent relationship is defined on the basis of whether a common boundary or interregional distance exists, and if great-circle/economic distance or transportation cost reflects travel time from one place to another. When deciding interregional distance, this study considers the significant development of railway and road systems, for example, G-series high-speed train lines, in cities with a population higher than 500,000, which will definitely reduce the time and cost of interregional exchanges of institutions, information, and industrial transfer, and increase spatial interaction strength. Considering data availability, the present analysis used minimum train arrival time for 30 provinces till May 30, 2017.

This study highlights five factors that influence the spatial interaction strength of total energy efficiency. First is industrial structure (IS). The related literature largely adopts the GDP of the secondary or tertiary industry. However, the energy consumption level tends to differ by industry; in the recent 2 years, the proportion of China's tertiary industry has exceeded 50%. Thus, it would be one-sided to examine the industrial structure level for each province using the proportion of one industry. Employing an industrial upgrading coefficient method, which has been increasingly used to measure industrial structure in recent years, this study assumes the upgrade level of provincial industrial structure to be 1 × provincial proportion of secondary industry + 2 × provincial proportion of secondary industry + 3 × provincial proportion of tertiary industry. The second influencing factor is transportation infrastructure (TI), expressed by the railway operating mileage of each province; the third is technical progress (TECH), which is replaced by transaction volume for each province's technical market. The fourth is the degree of government interference (GI), denoted by the ratio of local general budget expenditure to gross regional domestic product; and finally, FDI in each province during the study period was collected and converted into the constant value of 2000. Data for these factors are obtained from the China Statistical Yearbook, China Statistical Yearbook on Energy, China City Statistical Yearbook, China Statistical Yearbook on Environment, and statistical yearbooks of every province from 2000 to 2015.

Table 1 Statistical description of input and output indexes for 30 provinces

Index	Expression	Maximum value	Minimum value	Mean value	Standard error	Total
GDP (CNY100 million)	Y	49,708	263.68	8244.8	8091.7	450
Labor force (10,000 persons)	L	6670.4	273.9	2447.3	1643.7	450
Energy (10,000 t of standard coal)	E	35,363	479.95	10,010	7183.9	450
Capital stock (CNY100 million)	K	34,178	739	9198.2	6949	450
Industrial solid waste (10,000 t)	sw	45,576	75	6412.592	6682.85	450
Industrial emissions (billion cubic meters)	$T = 30$	79,121.3	434	13,180.05	12,338.98	450
Industrial waste water (10,000 t)	t_{max}	838,551	3453	94,177.98	99,923.89	450

Total factor energy efficiency for each province

The values of total factor energy efficiency for the 30 Chinese provinces during 2000 and 2014 are obtained using MaxDEA 6.0. Table 3 presents the results for the efficiency change (EC) index, technology change (TC) index, and Malmquist–Luenberger index, as well as the mean values.

Table 3 indicates the following trends for average total factor energy efficiency in China during 2000 and 2014. Ningxia, Inner Mongolia, and Qinghai report the highest total factor energy efficiency, of which Ningxia has the highest mean value of 1.196, with an increase of 19.6%. All three provinces are in northwest inland of China, where economic development lags, there are few industrial enterprises, and the environmental quality and energy consumption are better than those in developed areas. The ML index is bounded by 1, and its results indicate that total factor energy efficiencies for 19 provinces during the period examined are on the production frontier. The gaps in the ML index for mid-level provinces (i.e., those ranking 9–19) are small, and the maximum is 2.3%. In addition, Beijing, Liaoning, Anhui, Hainan, and Guangxi appear to be falling behind, of which Hainan's factor energy efficiency is 78% and descended by 22%, which is significantly lower than those of other provinces (Table 4).

Figure 1 illustrates that the growth in the average total factor energy efficiency of the western region is perennially higher than those of other regions and the entire nation, which is also consistent with the results in Table 4. However, prior to 2009, changes in total factor energy efficiency were not stable. The energy efficiency in the middle region fluctuated most

closely to the national average, and the ML index was the most stable with a mean of 0.998. In the eastern region, the total factor productivity fluctuated greatly. It declined rapidly from 2000 to 2002, and reached a low level from 2002 to 2005, after which it rose to a stable state, with the exception of 2010–2011, when the total factor productivity retained stable status.

Spatial interaction strength

Since the data for spatial interactions constantly change, whereas the present index is a static result, first, this study calculates each year's value, and then compares them. This discussion is limited to the potential values of each province's energy efficiency for specific years owing to space constraints. Table 5 presents the results.

The table shows that the top ranking of Gansu, Inner Mongolia, Qinghai, and Ningxia did not fluctuate, and for mid-level provinces like Henan, Heilongjiang, Hubei, and Shandong, the fluctuation trends are the same. Provinces with a significant increasing trend in recent years are Tianjin (from 28th to 5th), Chongqing (from 17th to 8th), and Qinghai (from 14th to 4th). It is noteworthy that, in 2012, the decline in spatial interaction strength in Jiangsu Province (from 16th to 25th) and Anhui Province (from 6th to 27th) coincided with that in total factor energy efficiency change in the eastern region. In addition, the rankings for Heilongjiang, Liaoning, and Jilin marginally decreased, while the spatial interaction strength for Inner Mongolia increased by 141.3% to 113.36 in 2003 than 46.98 in 2002.

Table 2 Territory classification

Location	Province
East	Beijing City, Tianjin City, Hebei Province, Liaoning Province, Shanghai City, Jiangsu Province, Zhejiang Province, Fujian Province, Shandong Province, Guangdong Province, Hainan Province
Middle	Shanxi Province, Jilin Province, Heilongjiang Province, Anhui Province, Jiangxi Province, Henan Province, Hubei Province, Hunan Province
West	Inner Mongolia, Guangxi Zhuang Autonomous Region, Chongqing City, Sichuan Province, Guizhou Province, Yunnan Province, Shanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region

Table 3 Evaluation results for total factor energy efficiencies for 30 Chinese provinces (2000–2014)

Province	EC index	TC index	ML index	ML ranking	Province	EC index	TC index	ML index	ML ranking
Anhui	1.004	0.959	0.963	24	Liaoning	0.995	0.948	0.943	27
Beijing	0.998	0.921	0.919	28	Inner Mongolia	1.068	1.076	1.149	2
Fujian	0.999	0.993	0.992	22	Ningxia	0.976	1.224	1.196	1
Gansu	1.065	1.006	1.072	5	Qinghai	0.995	1.151	1.146	3
Guangdong	0.998	1.000	0.998	20	Shandong	0.993	1.001	0.994	21
Guangxi	1.014	0.795	0.806	29	Shanxi	1.004	1.017	1.021	10
Guizhou	1.001	1.037	1.039	6	Shanxi	1.007	1.011	1.018	13
Hainan	1.008	0.774	0.780	30	Shanghai	1.000	1.000	1.000	19
Hebei	0.996	1.008	1.003	18	Sichuan	0.999	1.006	1.006	17
Henan	0.999	1.025	1.023	9	Tianjin	1.021	1.050	1.073	4
Heilongjiang	1.004	0.976	0.979	23	Xinjiang	0.998	1.032	1.030	8
Hubei	0.997	1.010	1.007	16	Yunnan	1.004	1.016	1.020	11
Hunan	1.002	1.033	1.035	7	Zhejiang	0.997	1.016	1.013	14
Jilin	1.006	1.003	1.009	15	Chongqing	1.007	1.012	1.019	12
Jiangsu	0.967	0.981	0.949	26	Mean value	1.004	0.997	1.002	–
Jiangxi	1.013	0.938	0.950	25	–	–	–	–	–

– data are unavailable

Spatial econometric model results

Spatial autocorrelation test

In this section, Stata 14.2 is used to calculate Moran's index for the potential values of the total factor energy efficiencies in 30 provinces. Table 6 presents the results.

The results show that the values for Moran's I in each year are greater than 0, indicating that the potential values of total factor energy efficiencies for each province have a spatial positive correlation. The statistical values for Moran's I during

Table 4 ML index mean values for each Chinese region

Year	The whole nation	East	Middle	West
2000–2001	1.010	1.386	0.973	1.034
2001–2002	1.014	0.930	0.972	1.093
2002–2003	1.023	0.975	1.003	1.147
2003–2004	1.028	0.944	1.009	1.095
2004–2005	1.004	0.942	0.980	1.047
2005–2006	1.011	1.073	0.980	1.040
2006–2007	1.005	1.056	0.986	1.035
2007–2008	1.006	0.992	0.985	1.002
2008–2009	0.996	1.022	0.981	1.050
2009–2010	1.008	1.020	0.994	1.061
2010–2011	1.013	0.863	1.203	1.091
2011–2012	0.968	0.999	1.009	1.018
2012–2013	0.988	1.068	1.005	1.015
2013–2014	1.018	1.006	0.995	1.031
Mean value	1.006	0.969	0.998	1.045

the 12-year research period ranged between 0.058 and 0.267, and were significant at the 10% level. Thus, we can conclude that the spatial interaction of total factor energy efficiency for all provinces is not completely random, but is in a positively related state of spatial dependence. In addition to local economic development, industrial restructuring, resource consumption, technological development, and increased environmental regulation strength in adjacent regions could affect the strength of total factor energy efficiency for all provinces, and intensify the spatial correlation.

Scatter diagram for local autocorrelation

On the basis of the aforementioned discussion, Fig. 2 presents a four-quadrant Moran's I scatter diagram for the potential values of total factor energy efficiency for 30 provinces in select years.
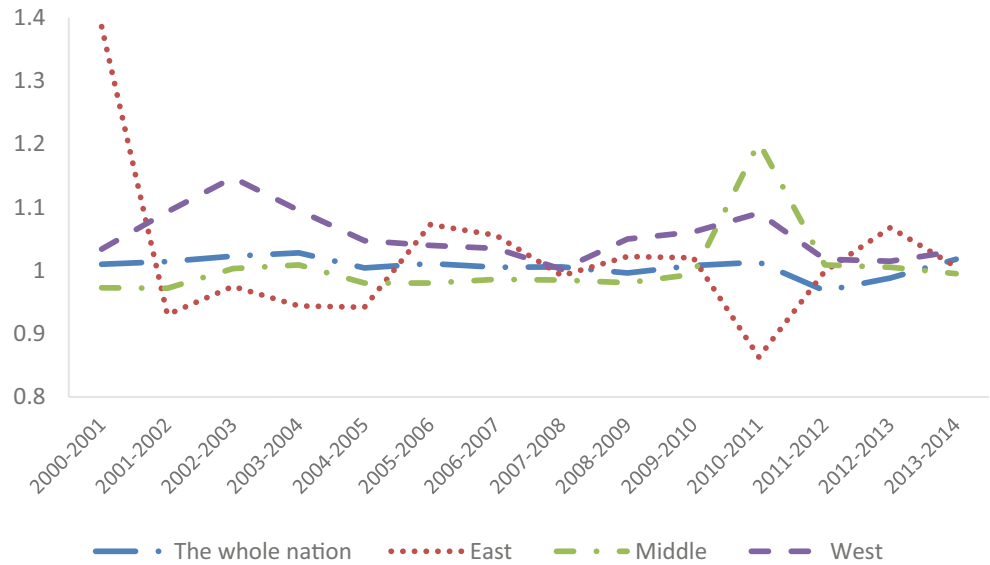
The scatter diagram reveals that, in the selected 4 years, two thirds of the provinces are in the first and third quadrants, thus proving the existence of spatial positive correlation or the spatial dependence of the potential value for total factor energy efficiency among the provinces. Most provinces demonstrate a clustering effect on adjacent provinces, and the potential values for the remaining provinces are atypical.

In 2011 and 2014, Inner Mongolia, Gansu, and Ningxia are in the first quadrant, of which Inner Mongolia and Qinghai show an increasing trend to the first quadrant in 2008 and 2011. Inner Mongolia jumps from the fourth quadrant to the first quadrant in 2009. These four provinces also rank among the top four in terms of spatial interaction strength of total factor energy efficiency, indicating a high-high (H-H; high strength of energy efficiency integration and high spatial lag)

Fig. 1 Change trend for total factor energy efficiency

positive autocorrelation clustering mode. Provinces with spatial interaction of high strength are surrounded by provinces with high spatial interaction strength.

Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Sichuan, Shanxi, and Xinjiang are located in the second quadrant, and report a clustering low-high (L-H; low strength of energy efficiency integration and high spatial lag) negative autocorrelation, of which Shanxi, Liaoning, and Xinjiang have low spatial interaction strength in terms of energy efficiency, and are surrounded by provinces with higher strength. Beijing, Shanghai, Jiangsu, Anhui, Zhejiang, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, and Yunnan lie within the third quadrant, and the potential values of total factor energy efficiency rank low. Most of these regions are located in the low-low quadrant and East Chinese region; they meet the condition that provinces with low spatial interaction strength are surrounded by provinces with higher strength. Tianjin is in the fourth quadrant, while Guizhou stretches across both the third and fourth quadrants.

Referencing Rey's (2001) space time translation method, 17 provinces can be classified as HH→HH and LL→LL, and their transition is at the same level. The transition of Beijing Tianjin (LL→HH), Jilin and Shanxi (HH→HL), and Ningxia (HL→HH) is geographically of adjacent type. Inner Mongolia (LH→HH) and Hainan's (LL→HL) transitions can be termed as relative displacement. Guizhou stretches across the two quadrants and thus belongs to an atypical type. Qinghai is in the second quadrant in 2005 and 2014, stretches across the first and fourth quadrants in 2011, and reaches the fourth quadrant in 2012 and 2014, rendering it an unstable region.

Solution of spatial econometric model

According to the above analysis, the explained variables in this study may have time inertia, that is, one region may become the "supply region" of demand in the early phase, and exert an appealing force on adjacent regions. Such an appealing force may persist throughout the current period. When using the model with fixed time and individual effects, to avoid endogeneity resulting from the first-order lag term of the dependent variable being the explained variable and the spatial spillover effect, this study adopts the space Durbin model for parameter estimation. Tables 7 and 8 present the results for the entire nation, as well as the east, west, and middle regions, calculated using Stata 14.2.

From above regression results, we can draw the following conclusions. First, the one-order-lagged potential value for total factor energy efficiency is significant at the 1% level. The regression coefficient is positive, indicating that the previous year's economic development level, environmental improvement, and policymaking among provinces had a significant positive effect on the current year's energy efficiency potential value. Regression coefficient ln$cyjg$ for the spatial lag term of the explained variable is not significant as per the regression model. The study attempted to set an economic distance matrix (the value of every factor in the matrix is expressed by the product of the reciprocal of the square of the geographical distance between two regions and the ratio of local average GDP to national total GDP) to perform a regression on the space Durbin model, and derived a regression coefficient ln$jtss$ of 0.039, and a p value of 0. This indicates that the spillover effect of the potential value for total factor energy efficiency for all provinces is significant when provinces have similar economic development levels.

Second, the industrial structure variable has a significant negative effect on the potential value of the regional and provincial total factor energy efficiency; it is significant at the 1% level. However, when testing the eastern, western, and mid-regions, the industrial structure level positively impacts the potential values of total factor energy efficiency across all regions, especially in the west. This further highlights

Table 5 Potential energy efficiency values for each Chinese province (select years)

Province	Potential value	Ranking (2001)	Potential value	Ranking (2005)	Potential value	Ranking (2011)	Potential value	Ranking (2014)
Beijing	20.27	22	35.33	23	38.91	15	15.95	16
Tianjing	18.51	29	45.98	5	124.54	2	127.13	3
Hebei	20.46	20	36.75	16	45.29	8	53.15	10
Shanxi	20.55	19	26.15	27	53.81	5	66.66	4
Inner Mongolia	22.37	5	226.19	1	290.47	23	334.25	28
Liaoning	21.16	13	19.81	28	16.99	3	23.24	2
Jilin	21.39	10	39.51	9	48.54	19	58.93	19
Heilongjiang	21.41	9	28.19	25	42.19	10	39.23	9
Shanghai	20.71	16	35.78	21	44.20	30	50.99	30
Jiangsu	20.71	17	36.64	18	28.07	6	24.98	7
Zhejiang	20.81	15	37.17	12	55.83	24	61.47	24
Anhui	20.26	23	37.02	13	35.12	22	30.27	22
Fujian	19.93	27	36.73	17	39.74	17	46.00	17
Jiangxi	15.14	30	26.90	26	15.05	14	25.37	13
Shandong	20.12	24	28.66	24	28.98	7	46.44	6
Henan	20.02	26	35.99	20	59.48	29	67.82	29
Hubei	20.08	25	36.41	19	48.35	20	55.40	20
Hunan	20.36	21	36.88	14	69.99	28	79.98	25
Guangdong	20.70	18	35.55	22	43.36	12	50.40	11
Guangxi Zhuang Autonomous Region	22.37	4	14.59	29	2.76	1	2.56	1
Hainan	114.70	1	3.34	30	0.54	9	1.63	8
Chongqing	21.19	12	39.34	10	55.67	26	67.37	26
Sichuan	21.31	11	38.33	11	49.84	11	56.55	14
Guizhou	21.07	14	40.98	7	63.75	16	85.44	15
Yunnan	21.44	8	39.55	8	56.25	21	69.31	23
Shanxi	19.55	28	36.86	15	51.37	25	62.65	21
Gansu	22.36	6	73.51	2	107.76	4	137.95	5
Qinghai	23.05	2	66.81	4	264.67	13	347.48	12
Ningxia Hui Autonomous Region	22.59	3	67.06	3	470.36	18	618.65	18
Xinjiang Uygur Autonomous Region	21.89	7	41.97	6	57.24	27	79.96	27

China's development strategies, industrial transfers in the mid- and western regions, and the advantages of the "One Belt One Road" initiative in these regions. The industrial structure coefficient in the eastern region is the lowest, indicating that the blind pursuit for industrial upgrading may not improve the potential value for energy efficiency because of the high

Table 6 Moran's *I* for potential values of China's provinces, 2000–2014

Year	2000	2001	2002	2003	2004	2005	2006	2007
→	0.395	0.038	0.216	0.038	0.006	0.004	0.041	0.091
Z value	3.85	2.128	2.396	1.015	0.749	0.592	1.03	1.474
P value	0	0.017	0.008	0.155	0.227	0.277	0.151	0.07
Year	2008	2009	2010	2011	2012	2013	2014	–
→	0.117	0.182	0.193	0.15	0.144	0.157	0.154	–
Z value	1.474	2.238	2.505	1.965	1.919	2.063	2.068	–
P value	0.07	0.013	0.006	0.025	0.027	0.02	0.019	–

– data are unavailable

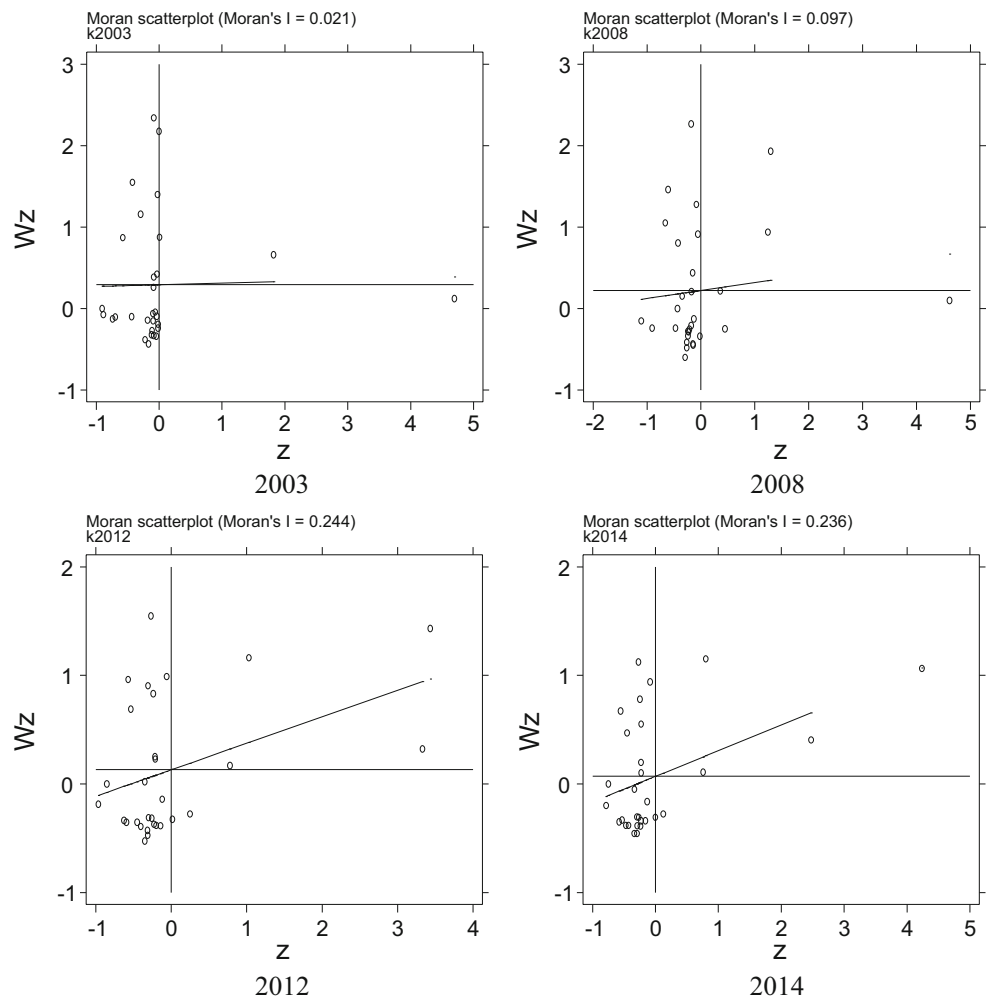**Fig. 2** Moran's *I* scatter diagram for potential value of energy efficiency (select years)

2003

2008

2012

2014

Table 7 Regression results for spatial dynamic panel Durbin model

Variable	The whole nation	East	Middle	West
$\ln T_{i,\,t-1}$	1.091*** (56.75)	1.092*** (21.00)	0.972*** (18.84)	1.080*** (50.76)
$W \cdot \ln T_{i,\,t-1}$	− 0.346* (− 1.84)	− 0.118 (− 1.42) 2.26**)	0.528 (1.00) 2.437	0.395*** (12.13)
lnIS	− 1.180*** (− 4.05)	2.26** (2.26)	2.437*** (7.03)	15.071*** (31.24)
lnTI	0.545 (1.48)	0.486 (0.64)	0.108* (1.82)	− 0.167*** (− 3.37)
lnTECH	− 0.556*** (− 2.82)	− 0.558 (− 1.43)	0.743* (1.9)	− 0.333*** (− 12.86)
lnGI	0.173* (1.66)	0.492 (1.92)	0.155 (0.75)	0.523*** (4.34)
lnFDI	0.256 (0.43)	− 0.616*** (− 3.88)	− 0.212* (− 1.68)	1.243*** (14.48)
W*lnIS	0.427*** (3.6)	2.619*** (3.14)	0.849*** (4.29)	3.191*** (13.88)
W*lnTI	− 0.192* (− 1.71)	− 0.046 (− 0.09)	− 0.432 (− 1.61)	0.002 (0.13)
W*lnTECH	0.110 (1.44)	− 0.242 (− 0.86)	− 0.419** (− 2.11)	− 0.231*** (− 16.45)
W*lnGI	0.106** (2.11)	0.393 (1.28)	− 0.309** (− 2.59)	− 0.198*** (− 3.03)
W*lnFDI	− 0.484** (− 2.27)	− 0.192 (− 1.40)	0.329 (0.54)	− 0.556* (− 1.87)
ρ	0.008 (0.43)	−	−	−

Values in parentheses are Z statistic values

*Significance at the 10% level; **significance at the 5% level; *** significance at the 1% level

Table 8 Breakdown table of spatial effect

Region	Classification of effect	lncyjg	lnjtss	lnjsjb	lnzfgy	lnfdi
The whole nation	Short-term average direct effect	−1.037 (−1.18)	0.472*** (3.38)	0.193*** (5.27)	−0.797*** (−3.88)	−0.229* (−1.73)
	Short-term average indirect effect	−4.153* (−1.70)	−0.160 (−0.75)	0.031** (2.35)	−0.391 (−0.79)	0.577 (1.57)
	Short-term average total effect	−5.19* (−1.89)	−0.312 (1.42)	0.506*** (3.23)	−1.188** (−2.32)	−0.349 (0.92)
	Long-term average direct effect	−1.474 (−0.74)	1.117*** (3.32)	0.375*** (5.21)	−1.740*** (−3.51)	−0.650** (−2.01)
	Long-term average indirect effect	−3.472 (−1.27)	−0.721** (−2.22)	0.128 (1.00)	−0.474 (0.76)	−0.911** (2.00)
	Long-term average total effect	−4.947* (−1.91)	−0.396* (1.86)	0.504*** (3.42)	−1.267*** (−2.64)	−0.260 (0.74)
East	Short-term average direct effect	−1.029 (−0.38)	0.220 (0.83)	0.354*** (4.12)	−2.840*** (−6.22)	0.056 (0.22)
	Short-term average indirect effect	1.078 (0.23)	0.555 (1.48)	0.805**8 (3.00)	0.250 0.27	−0.698 (−1.26)
	Short-term average total effect	0.050 (0.01)	0.776** (2.01)	1.160*** (3.67)	−2.590*** (−2.63)	−0.642 (−0.99)
	Long-term average direct effect	−1.712 (−0.41)	0.165 (0.39)	0.291** (2.52)	−4.087*** (−5.47)	0.260 (0.70)
	Long-term average indirect effect	1.590 (0.31)	0.446 (1.01)	0.627** (2.53)	1.750* (1.75)	0.730 (−1.34)
	Long-term average total effect	−0.120 (−0.03)	−0.611** (2.03)	0.918*** (3.88)	−2.338*** (−3.10)	−0.471 (−0.94)
Middle	Short-term average direct effect	0.296 (0.27)	0.072 (0.49)	−0.044 (−0.49)	0.14 (0.40)	0.218 (1.01)
	Short-term average indirect effect	4.472 (1.52)	−0.098 (−0.37)	0.021 (0.09)	−0.571 (−0.69)	0.334 (0.57)
	Short-term average total effect	4.768 (1.27)	−0.026 (−0.09)	−0.023 (−0.07)	−0.429 (−0.42)	0.552 (0.77)
	Long-term average direct effect	−1.781 (−0.75)	0.259 (0.57)	−0.139 (−0.89)	0.739 (0.82)	0.417 (0.77)
	Long-term average indirect effect	5.347* (1.84)	−0.244 (−0.57)	0.101 (0.51)	−0.991 (−0.99)	−0.093 (0.14)
	Long-term average total effect	3.567 (1.17)	0.015 (0.06)	−0.037 (−0.14)	−0.252 (−0.29)	0.510 (0.87)
West	Short-term average direct effect	−1.500 (−1.01)	−0.001 (−0.01)	0.092 (1.99)	0.056 (0.20)	0.283 (1.40)
	Short-term average indirect effect	−15.12*** (−3.93)	−0.207 (−0.70)	−0.233 (−1.57)	−1.159** (−2.05)	1.98*** (3.83)
	Short-term average total effect	−16.62*** (−3.85)	−0.208 (−0.64)	−0.140 (−0.78)	−1.103* (−1.95)	2.263*** (3.73)
	Long-term average direct effect	−0.117 (−0.04)	0.039 (0.10)	0.240*** (2.79)	0.348 (0.57)	0.199 (0.634)
	Long-term average indirect effect	−18.09*** (−3.69)	−0.266 (−0.62)	−0.380** (−2.25)	−1.535* (−1.88)	2.294*** (3.61)
	Long-term average total effect	−18.21*** (−3.75)	−0.227 (−0.62)	−0.140 (−0.70)	−1.18* (−1.89)	2.493*** (3.60)
	Short-term average direct effect	lncyjg	lnjtss	$H_k(w)_{ij}$	T_i	i

economic development levels and complete industrial structure. This also explains the negative coefficient when considering industrial structure within the nationwide range.

Third, the effects of transport infrastructure and technical progress on the potential values of total factor energy efficiency were significant at the 1 and 10% levels. The construction of highways, railways, and civil aviation route networks will enable provinces to reach the maximum effect of interconnection. The costs of such links as technology exchange, population migration, commodity circulation, industrial transfer, and policy learning will also decrease in these provinces, directly enhancing the spatial interaction intensity of total factor energy efficiency. During the industrial transfer, eight provinces in the mid-region underwent an upgrading process from the primary to the secondary industry. Given a large proportion of industrial enterprises, industrial enterprise clustering can boost local economic development and potential value in the short term. However, in the long run, industrial enterprises are mostly pollutive. Thus, improvements in scientific and technological levels could improve productivity and reduce energy consumption. However, at the same time, they can reduce enterprises' treatment cost, which is favorable to enterprises' operating activities, and counters governmental environmental regulations. The west has the highest technical progress coefficient with a high significance level and p value of 0. This is because the west has been in a state of lag, and technological development in the region seems to have an instant effect.

Fourth, of the five independent variables, FDI and degree of government interference negatively affected the potential value of China's total factor energy efficiency; they pass the 10% significant test. On the other hand, the mid- and western regions passed the significance test. At present, in addition to FDI, governmental fiscal expenditure in the western region also promotes GDP growth. This is also reflected in the values of independent variable coefficients. The coefficient of government interference is the second largest independent variable after industrial restructuring to affect the potential value of total factor energy efficiency in the west.

The regression coefficients for the space Durbin model are not the elastic coefficients of explained variables. In Eq. (14), $H_k(w)_{ij}$ is used to measure the influence of change in independent variables on the observed value of the explained variable and that of the observed value on itself in the feedback circuit. The effects are divided into short- and long-term influences. The effect of explained variable T_i caused by a change in the ith observed value for the kth explained variable is called the average direct effect, and the effects on other regions are called spatial spillover effect (average indirect effect). See Table 8 for details.

Fifth, judging from the nationwide range, the direct effects of other independent variables, except FDI, have contrary

results in the short and long term. For example, the economic environmental benefits from industrial regulations may not have direct short-term effects; even areas with strict environmental regulations may compel industrial enterprises to exit the regions, resulting in the slowing down of economic development. However, in the long run, the optimization of proportions of various industries and restrictions on high energy-consuming and highly pollutive enterprises could positively stimulate the potential value of total factor energy efficiency in China. Another example is the degree of government interference. An increase in the general budge expenditure for local finance would increase local economic governance in the short term, promote technical progress, and improve the production efficiency of industrial efficiencies. However, long-term dependence of the local government on government expenditure will reduce productivity and economic growth, which, in turn, will hinder the potential value of total factor energy efficiency in the corresponding area.

Sixth, the spatial effect produced by the increase of FDI in the western region all passed the significance test at the 1% level, indicating high investment potential in western China. However, examining the spatial effect of FDI in the whole country shows results that are contrary to those of the western region, which needs further research (Table 8).

Finally, technical progress has the best spatial effect across all provinces. Irrespective of the direct or spillover effect, it has a positive influence on adjacent regions. Technical development, R&D input, and clean energy technology have a direct bearing on the environmental performance of each province. The value of the long-term average indirect effect, 0.128, is considerably higher than that of the short-term average indirect effect, 0.031. This indicates that, in addition to increased technological levels significantly improving the potential value of total factor energy efficiency in the short run, such an influence persists in both the relevant and adjacent areas.

Conclusions and implications

Conclusions

This study adopts a nonradial and slack variable perspective, and employs a super-efficiency SBM–DEA model to calculate the total factor energy efficiency of 30 Chinese provinces during 2000–2014. Since total factor energy efficiency has a spatial spillover effect, by referencing Wilson's maximum entropy model, this analysis attempted to set up a model to calculate the strength of spatial interactions that are based on energy efficiency, which is also known as the potential value for total factor energy efficiency. After testing for the existence of the spatial positive autocorrelation of the potential value for total factor energy efficiency, a space Durbin model

was set up to examine influencing factors, including industrial structure, energy strength, and technical progress.

For the period of 2000–2014, 16 provinces reported mean values for the ML index that were greater than 1. Provinces with front rankings are located in the Northwest China, where there are few industrial enterprises, and environmental pollution is low. According to the calculation results for the potential value of total factor energy efficiency, the abnormal fluctuation in the ML index during 2003 and 2012 tallied with those of rankings of the potential value for each province's energy efficiency in terms of time and location. This study also adopted Moran's I scatter diagram to observe the clustering effect of the potential value of all provinces' total factor energy efficiency. It shows that the transitions of 22 provinces were of the same type. However, the industrial structure of the three major eastern, central, and western regions has a positive effect on the total factor energy efficiency potential of all regions.

Implications

Based on the empirical results in the article, the following implications can be drawn:

1. *Optimize economic structure and improve energy efficiency.* Currently, China still has low energy efficiency. In some areas, it is far away from the production front of DEA, and there is still substantial room for improvement in energy efficiency. According to the research in this article, the industrial structure and technological level have different impacts on energy efficiency. Therefore, accelerating the structural adjustment is conducive to China's economic restructuring and energy efficiency.

2. *Improve the technical level and promote energy conservation.* One of the main reasons for the low energy efficiency in China is the excessive emission of pollutants. According to this research, the emission of unwanted pollutants from energy sources limits the energy efficiency improvement. Therefore, energy conservation and environmental governance need to be strengthened to enhance energy efficiency and achieve effective energy efficiency improvements.

3. *Strengthen regional coordination and promote common development.* According to the analysis in this paper, the energy efficiency in the western region is higher than that in the middle and eastern parts of the country, and there is a direct impact and spillover effect between regions. Therefore, it is necessary to strengthen the coordination of regional energy issues on environmental governance and give full play to the exemplary role of energy-efficient regions for energy efficiency improvement.

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