Measurement and Structural Factors Influencing China’s Provincial Total-Factor Energy Efficiency Under Resource and Environmental Constraints

Hongzhang Chen1 and Haiwen Yang2

Abstract

We studied the measurement and structural factors influencing China’s provincial total-factor energy efficiency (TFEE) under resource and environmental constraints, using spatial weight matrix analysis, spatial econometric model selection, a generalized spatial econometric model with unknown heteroscedasticity, and a directional distance function global Malmquist–Luenberger (GML) superefficient model. The findings of this empirical research are as follows. Resource and environmental constraints should be considered while measuring TFEE. The results obtained in such cases are more accurate reflections of the actual situation in China. Furthermore, spatial effects should be considered when analyzing the factors influencing provincial TFEE; otherwise, the estimates will be biased. The following conclusions were obtained from the results of the empirical analysis: China’s provincial TFEE continued to decline under resource and environmental constraints, and the trend is not optimistic, implying an undue reliance on coal resources, which reduce TFEE by a considerable extent. Moreover, China’s interprovincial TFEE is affected by a variety of structural factors.

Keywords

total-factor energy efficiency, directional distance function, global Malmquist–Luenberger superefficient model, generalized spatial model, Markov chain Monte Carlo method

Introduction

The need for energy efficiency has been increasingly recognized from 1970 onward. The oil crisis of the 20th century has only underscored the urgency of the problem. The International Energy Agency (IEA), which was founded as a response to the oil crisis, released a report entitled “Redrawn Energy and Climate Map” in 2013, which pointed out that globally, energy from carbon grew by 1.4% in 2012, and will reach a record high of 31.6 billion tons by 2020. Greenhouse gas emissions in the energy sector account for two thirds of global emissions. Thus, it is evident that issues related to energy constitute a serious problem, affecting global development. Hence, it is crucial to study this issue in more detail at the global scale.

Obviously, the blind pursuit of economic development is environmentally unsustainable and will inevitably lead to excessive waste of resources, extensive use of energy, and environmental degradation and depletion. China has had some remarkable achievements in economic development, but the development model has been labeled as high-investment, high-energy-consuming, high-growth, highly polluting, and inefficient. As a developing country, the contradictions between economic development, resource utilization, and environmental protection are particularly prominent. While China has a large population, it is relatively poor in resources and less technologically advanced. Its extensive economic development model in the past was naturally chosen as the norm for overall development. However, the government has understood the need to control environmental pollution, reduce energy consumption, improve the efficiency of economic development, and change the mode of economic growth. The country’s “11th Five-Year Plan” and “12th Five-Year Plan” are rising to the challenge of saving energy through consumption reduction targets, which comes at the cost of economic development. From 2006 to 2013, the government...
introduced 383 national-level environmental economic policies and 713 provincial-level environmental economic policies, including the environmental fiscal policy, environmental tax policy, and environmental resources pricing policy. Thus, environmentally inclined economic policies comprised 66.9% of the total. In 2014, the government also issued “Notice on the Adjustment of Sewage Charges, Levied Standards, and Other Related Issues,” which referred to doubling the collection fees for emissions and sewage generation, among other points.

Clearly, China has started to implement more stringent environmental policies and environmental quality standards, and continues to increase the intensity of its energy-saving and emission reduction measures by decreasing energy consumption, slowing the development of energy-intensive industries, and encouraging the manufacture and use of energy-efficient products. To achieve sustainable economic and social development, the Chinese government aims to build a resource-saving and an environment-friendly society, which would be geared toward changing the country’s current mode of socioeconomic development. Improving energy efficiency is thus a core aspect for meeting two types of social goals set by the government.

However, economic development is inseparable from energy consumption. Energy consumption entails carbon emissions, which affect the external environment and, in turn, the quality of economic development. Obviously, improving energy efficiency is intended to reverse environmental depletion and degradation as well as achieve the development of a green economy for China. The IEA (2010) has also pointed out that energy inefficiency is the largest contributor to carbon emissions.

Conventionally, the ratio of energy consumption to economic output has been viewed as an indicator of energy efficiency (e.g., energy consumption intensity is estimated as energy consumption per unit of gross domestic product or GDP) and it was believed that lower energy consumption reflects higher energy efficiency. This definition was actually referred to as single element of energy efficiency. However, this approach does not take into account other factors of production efficiency and alternative sources of energy, and thus, it is an unreasonable measure of energy efficiency. Thus, currently, total-factor energy efficiency (TFEE) indicators are used, which are comprehensive in that they consider energy inputs and other elements that interact with the same; hence, the results are closer to the true values and more reliable.

Malmquist and Shephard (1953) independently developed the distance function concept. It involves constructing a decision-making unit’s (DMU’s) actual production and distance from the production frontier to reflect the productivity of that DMU. A smaller distance indicates high production efficiency and vice versa. However, the distance function framework could not perform as intended in the presence of “bad” outputs. Shephard (1970) presented an output-oriented distance function, which could be applied to both “good” and “bad” outputs. The production efficiency of the DMU is reflected by the distance between the actual production state of the DMU and the production frontier. The smaller the distance, the higher the production efficiency. However, when two outputs are in the same direction they do not meet the requirement of “good” output and decrease “bad” output. Therefore, these techniques are not applicable to energy efficiency evaluations pertaining to resource and environmental constraints. Cook et al. (2009) proposed a feasible variable returns to scale (VRS) super-efficiency model with input- and output-oriented VRS, but Cheng (2014) suggested that this model has no feasible solution as its superefficiency formula is flawed. Accordingly, this study uses Cook et al.’s (2009) method. TFEE is originally defined as the target energy input divided by the actual energy input. When considering non-radial slack, TFEE can be analyzed in a single-factor framework. Integrating the concept of TFEE with the Malmquist productivity index. Hu and Chang (2009) proposed the total-factor energy productivity index (TFEPI) to investigate energy productivity changes in regions of China. Honma and Hu (2009) extended their previous work by applying TFPI. The acronym TFEE in the article is the same as in Hu and Chang’s (2009) TFEPI. Zhao et al. (2014) built an input-output framework based on a data envelopment analysis (DEA) window aimed at exploring TFEE in 30 administrative regions and six areas across China from 2006 to 2012. Hu and Wang (2006) and Zhang et al. (2011) used the DEA method to study TFEE of regions in China and developing countries, respectively. Pang et al. (2015) analyzed the effects of clean energy use on total-factor efficiencies, simultaneously considering economic output, energy conservation, and emission reduction. Q. Wang et al. (2013) used meta-frontier DEA approach to analyze energy efficiency and production technology heterogeneity by considering the “technology gap” in China. Hang et al. (2015) discussed energy inefficiency with undesirable outputs and technology heterogeneity in Chinese cities by using the non-radial slacks DEA model. The Chinese cities were divided into four categories and different strategic policy analysis were given. H. Wang et al. (2017) used an extended non-parametric frontier approach to measure energy efficiency and productivity performances with sectoral heterogeneity. Z. Chen et al. (2019) developed energy congestion DEA models (UEC and DEC) to get undesirable and desirable energy congestion measurements, and detected the technical ineffectiveness of regional coal-fired power generation industry in China.

The existing literature indicates that many areas of TFEE require focused research. The majority of the literature does
not consider resource and environmental constraints, or considers one without referring to the “bad” effects of output. In some cases, studies may be restricted to the “bad” effects of output, or the DEA model selection may pose problems (e.g., the model may be too simple). Not all factor analyses refer to energy efficiency, or the econometric model may be too simplistic. Thus, this study considers resource and environmental constraints, and to do so, it uses a directional distance function global Malmquist–Luenberger (GML) superefficient model with unknown variances for the estimation of TFEE. Only such a broad analysis of the factors influencing the spatial econometric model allows us to provide sound policy advice.

The Introduction of the Method
The Malmquist–Luenberger Superefficient Model
The energy efficiency calculation in this study is conducted using a directional distance function GML superefficient model. To begin with, the superefficiency model is based on the first distance function. As it is more directly in the production function it is unable to input, multiple-output production of technical analysis. To solve the abovementioned problems, Chung et al. (1997) established a directional distance function based on the Malmquist–Luenberger (ML) index, which defined the direction vector to specify the direction of the improvement of the input and output indicators. However, the total-factor productivity calculated by the geometric mean using the ML index does not have cyclic multiplicative. It can only analyze the short-run variation of production efficiency in the adjacent period and cannot observe the long-term growth trend of production efficiency. Moreover, the mixed directional distance function cannot easily provide a feasible linear programming solution. The GML approach, which is based on a global production technology set, can effectively avoid linear programming defects. At the same time, a continuous production frontier avoids the possibility of the production frontier shifting inward, that is, it avoids the possibility of a “technical regression” phenomenon. Many DMUs are valid simultaneously (the efficiency value is 1) in the GML model of directional distance function, which makes further comparison impossible. The superefficiency DEA approach can make up for this defect. Thus, the general DEA model divides the DMUs into effective and ineffective ones, with the efficiency of the effective DMUs being 1, and these cannot be evaluated further and compared. In contrast, while evaluating a DMU, the superefficiency DEA model excludes itself from the set of DMUs and enables an effective comparison between them. Thus, it is necessary to be vigilant about the possible lack of a feasible solution when using superefficiency models. This study uses the VRS superefficiency model, and some DMUs have no feasible solution for certain years. The model can then be formulated as:

\[
\begin{align*}
\min & \beta \\
\text{s.t.} & \sum_{j=1,j\neq k}^n \lambda_j x_{ij} + \beta g_{ij} \leq x_{ik} \\
& \sum_{j=1,j\neq k}^n \lambda_j y_{ij} - \beta g_{ij} \geq y_{ik} \\
& \sum_{j=1,j\neq k}^n \lambda_j b_{ij} - \beta g_{ij} \leq b_{ik} \\
& \lambda \geq 0 \\
& i = 1,2,\cdots m; r = 1,2,\cdots q; j = 1,2,\cdots, n(j \neq k).
\end{align*}
\]

Where $\beta$ is an adjusting parameter, $\lambda$ denotes intensity variable, and $x$, $y$, and $b$, respectively, denote the inputs, the desirable outputs, and undesirable outputs. $x \in R^n_x, y \in R^n_y$, respectively, denote M-dimensional input vector and the N-dimensional “good” output vector. $b \in R^n_b$ denote J-dimensional “bad” output vector. Input vector $x$ can produce all output for manufacturing feasibility set $P(x)$:

\[
P(x) = \{ (y, b) : x \text{ can produce } (y, b), x \in R^n_x, y \in R^n_y, b \in R^n_b \}.
\]

It is necessary to pay special attention to the problem that there may be no feasible solution using the above superefficiency model, and some DMUs may have the problem of no feasible solution, in some years, when using the data of this article to analyze the GML superefficiency model of VRS. Cook et al.’s (2009) VRS superefficiency model with input and output orientation is proposed, but is rigid. Cheng (2014) thought that the VRS superefficiency model, proposed by Cook and others, has no feasible solution although a reasonable projection value can be obtained, but the calculation formula of its superefficiency is flawed. So, the correction is given, and this article makes a loan.

Spatial Weight Matrix and Spatial Econometric Model Selection
The spatial weight matrix is a real symmetric matrix used to represent the spatial positional relationship between spatial units (including spatial adjacency and spatial distance) and spatial attribute relationships (such as social and economic relations). Different spatial weight matrices reflect different economic principles and perspectives behind the research objects, as well as researchers’ different understandings of spatial effects.
The construction and selection of spatial weight matrix has a very important impact on spatial analysis. The ability to construct and select the appropriate spatial weight matrix is directly related to the final estimation and explanatory power of the model. Kostov (2010) pointed out that the spatial weight matrix constructed by researchers is usually related to their understanding of the problem analysis perspective and spatial effects. Zhu Pingfang et al. (2011) pointed out that in any empirical study of applied spatial econometric models, the setting of spatial weight matrix is a crucial part of the whole research. Y.-g. Chen (2009) pointed out that the final estimation results and explanatory power of the spatial econometric model are closely related to whether the spatial weight matrix can be constructed and properly selected. There are many methods for constructing the spatial weight matrix. For more detailed introduction, please refer to the doctoral thesis of the author Yang Haiven.

The choice of the spatial weight matrix can be combined with Moran Index (MI) test, Lagrange multiplier (LM) test, and Markov chain Monte Carlo (MCMC) method. First, adding the spatial weight matrix to ensure the spatial effect of the model, so you can use the MI test to analyze whether there is spatial effect, the MI test results significantly indicate that the model has spatial effects. In the case of spatial effects, the combination of the spatial weight matrix and the spatial econometric model should be further analyzed, and the LM test can be used. The method of the LM test is as follows: First, perform ordinary least squares (OLS) regression, obtain the residual of the regression model, and then perform LM diagnosis based on the residual. Calculate the standard LM-Error and LM-Lag statistic (i.e., the non-stable statistic form). If the two are not significant, keep the OLS results. In this case, the MI contradicts the LM test statistic. Generally, the MI is calculated to be distorted due to het- eroscedasticity and non-normal distribution; if one of them is significant, that is, if the LM-Error is significant, the spatial error model (SEM) is selected, and if the LM-Lag is significant, the spatial lag model (SAR) is selected; If both are significant, then a robust LM diagnosis is performed. In this case, the Robust LM-Error and Robust LM-Lag statistics need to be calculated. If the Robust LM-Error is significant, the SEM is selected. If Robust LM-Lag is significant, then choose the SAR. We found that the LM method is a bit cumbersome. In fact, this method can be more concise and accurate using the MCMC method because the MCMC method only needs to calculate the posterior probability of the model, and the model with the largest posterior probability is optimal.

The spatial econometric model is based on the combination of spatial weight matrix and variable in spatial model: SAR,

\[
y = \rho Wy + X\beta + \mu, \mu = \lambda W\mu + \epsilon, \epsilon \sim N\left(0, \sigma_{\epsilon}^2 I_n\right)
\]

and generalized space model (SAC). The SAC model is the most general spatial measurement model, and its model form is:

\[
y = \beta_1 y + X_1 \beta_1 + \mu, \mu = \lambda W_2 \mu + \epsilon, \epsilon \sim N\left(0, \sigma_{\epsilon}^2 I_n\right)
\]

where \(y\) is the explanatory variable and \(X\) is the explanatory variable matrix, \(W_1\) and \(W_2\) are spatial weighting matrices that can be different, \(\beta, \beta_1, \beta_2\) are regression coefficient matrices, \(\rho\) and \(\lambda\) are the parameters of the autoregressive and the random interference term autoregressive to be estimated.

There are several methods for spatial measurement model selection, including LM test, maximum likelihood function method, information criterion methods, Bayesian posterior probability method, and MCMC method. Log likelihood (LogL), likelihood ratio (LR), Akaike information criterion (AIC), and Schwartz criterion (SC) are often used in nonspatial models. When the model is selected, the principle of verification is the same in spatial measurement, but the calculation is more complicated. In the selection method of the spatial measurement model, the LM test based on OLS estimation residual is mainly effective for the selection of SAR and SEM models. It is particularly important to note that when the criterion of LM test cannot give a conclusion, the actual data should be further judged. The generation process is possible for other models. Based on the information criteria of the likelihood function value, there is also a situation in which the selection of the spatial measurement model cannot be accurately determined. The popular method of research in recent decades, MCMC, has shown its outstanding performance in the selection of spatial measurement models.

**MCMC Method**

The Bayesian method is based on the a priori information and sample information of the unknown parameters; the posterior information of the parameters is obtained according to the Bayesian formula and the method of inferring the unknown parameters according to the posterior information. The Monte Carlo method is a method we are familiar with and it is also called statistical simulation method. The MCMC
method is obtained by combining the Bayesian method and the Monte Carlo method. The most widely used MCMC methods in Bayesian analysis are Gibbs sampling method and Metropolis–Hastings (M-H) method. The core of the MCMC method is to obtain a suitable Markov chain, so that its stationary distribution is the target distribution to be sampled (the target distribution is generally a posterior distribution $\pi(\theta | x)$ in Bayesian analysis), while Gibbs sampling and MH sampling are two different algorithms used to generate the Markov chain.

**Empirical Analysis**

**Measured Data and Variables**

The basic data are mainly derived from the China Statistical Yearbook, China Regional Economic Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, China High-tech Industry Statistical Yearbook, and the data network. As data for Chongqing and Tibet were not available, these areas were excluded from the study.

Based on the analysis of the existing literature, we mainly chose three input variables and four output variables (two “good” outputs and two “bad” outputs), as follows. (a) The first input variable is labor (L). Obviously, the higher the labor input, the higher the contribution of production, and therefore, the labor force, to the input variables. The average annual employment indicators were used as the input for labor in this study. (b) The second input variable is capital investment (K), which is expressed by the annual average capital stock (100 million Yuan). The higher the capital investment, the larger the scale; thus, more output can be obtained. This study applied the capital stock data for 2007–2016, converted at 1990 prices, using the perpetual inventory method, which is a representative method for capital stock data as per Shan (2008). (c) The third input variable is energy (E). The use of energy consumption (million tons of standard coal) explains that although the energy input is the middle input, energy consumption is, however, the main “bad” source of output. Tone and Tsutsui (2010) also used energy consumption as an input variable. (d) “Good” output, also known as “good” output or “agree” output. This article divides the “good” output into the “physical” output (ER) and the “service” output (SAN), and uses the sum of the added value of the primary and secondary industries (billion) and the added value of the tertiary industry, and converts all at 1990 comparable prices. (e) “Bad” output, also known as “bad” output or “unhappy” output. Yuan et al. (2009) puts waste gas and other industrial waste, dust, SO$_2$, and six other kinds of emissions as “bad” output. As the energy-related air pollutants are mainly CO$_2$ and SO$_2$, these are commonly represented as “bad” output.

**Summary of Input-Output Variables**

The input-output variables were used to carry out some basic statistical analyses. The descriptive statistical results and input-output correlation matrix are shown in Tables 1 and 2, respectively.

Before the DEA analysis, it should be ascertained whether the input and output variables are suitable for the analysis. Banker et al. (1989) proposed a rule of thumb: The number of DMUs must be more than twice the sum of the number of input and output variables; otherwise, the efficiency of the discriminating capacity becomes weak. This study employs 29 DMUs, and the input-output index is 7. Thus, the required condition is satisfied. In addition, the DEA method requires the inputs and outputs to meet the “isotonicity” requirement. The input variables and output correlation analysis, based on the Pearson correlation coefficient in Table 2, can be seen through the input and output of 1%. The significance level test shows that when the input increases, the output will also increase, and thus, these variables may be used to build a DEA model for efficiency measurement.

**Results of TFEE**

Based on the directional distance function and GML super-efficiency model of China’s 29 provinces and cities from 1990 to 2016, which contain the “bad” energy efficiency of the
output calculation. The results show obvious differences in the efficiency and global efficiency of provinces and cities in China. The geometric mean of the efficiency values of each province is greater than the geometric mean of the global efficiency values. The results for the provinces and cities show obvious differences, indicating the heterogeneity between them. The efficiency and global efficiency values are significantly different between provinces and municipalities, mainly owing to their different reference sets used when calculating the result. In addition, the efficiency and global efficiency values show that most of the provinces have energy efficiency values lower than 0.6, indicating that China still has much improvement to make in terms of energy efficiency.

Comparisons of efficiency and global efficiency values for a country having regions with “bad” and “good” outputs can yield estimates of efficiency and global efficiency values that exclude “bad” outputs (see Figure 1). The efficiency and global efficiency values calculated for the “bad” output are significantly different, and these values are also significantly lower than those calculated when no “bad” outputs were produced. We first used Kruskal–Wallis and Bartlett to test the variance consistency. Note that the null hypotheses of both tests are homogeneity of variances, and Kruskal–Wallis chi-square is equal to 4.1852, p value is equal to .1234 and Bartlett’s K-squared is equal to 2.0951, p value is equal to .3508, which assumes the null hypothesis of the consistency of the variances, indicating that there is no significant difference in the variance between the two. Thereafter, using the bivariate mean difference t test of the same variance, we obtain \( t = 12.365 \) (\( p = .0000 \)), rejecting the null hypothesis that the two mean values are the same, indicating that the mean values of the two are different, that is, the two efficiency values are significantly different.

The efficiency and global efficiency values do not show a significant decline with time, whereas the corresponding values with “bad” output show a declining trend. In addition, efficiency values that do not contain “bad” output show a clear upward trend after a slow downward trend from 1990 to 1994, and a slow decline since 2004. On the contrary, the efficiency and global efficiency values calculated with “bad” output show a clear downward trend except for a small fluctuation during the whole year. Thus, it is evident that China’s energy efficiency trends are not optimistic. In addition, ignoring the constraints of energy resources will result

### Table 2. Correlation Matrix of the Input and Output Variables.

| Variable | K       | L       | E       | ER      | SAN     | CO₂     | SO₂     |
|----------|---------|---------|---------|---------|---------|---------|---------|
| K        | 1       | .8821***| .5156***| .962*** | .8834***| .7652***| .5246***|
| L        | .8821***| 1       | .678*** | .9015***| .8318***| .8062***| .7351***|
| E        | .5156***| .678*** | 1       | .7142***| .4629***| .483***  | .6993***|
| ER       | .962***  | .9015***| .7142***| 1       | .9631***| .7735***| .5938***|
| SAN      | .8834*** | .8118***| .4629***| .9631***| 1       | .5952***| .4926***|
| CO₂      | .7652*** | .8062** | .483*** | .7735***| .5952***| 1       | .8162***|
| SO₂      | .5246*** | .7351***| .6993***| .5938***| .4926***| .8162** | 1       |

Note. K = labor; L = capital stock; E = energy consumption; ER = first and second industrial added value; SAN = added value of the tertiary industry; CO₂ = carbon dioxide; SO₂ = Sulfur dioxide. * * *** indicates significance at the 10%, 5%, 1% level.

![Figure 1. The comparison of efficiency and global efficiency values.](image-url)
in overestimation of China’s energy efficiency and thus further analysis is required with regard to this distortion.

**Analysis of the Factors Influencing TFEE**

Based on the estimated TFEE, we analyzed the factors influencing TFEE.

**Factors Affecting TFEE**

Based on the completeness, rationality, and availability of existing research literature and data, we first selected variables that may have an effect on TFEE. They are as follows:

1. Level of economic development (per capita gross domestic product [PGDP]): In general, empirical research is used to estimate GDP or per capita GDP to assess economic growth or economic development. In this article, GDP per capita was used to express the level of economic development, and we used the constant price and logarithm transformation. Chen and Wang (2010) and Wang et al. (2011) argued that the level of economic development affects energy consumption patterns; the more economically developed regions will choose more clean and efficient energy.

2. Industrial structure: Local governments aim to adjust the industrial structure within a certain period of time as a means to save energy. We choose the tertiary industry output value as the proportion of GDP as a proxy for industrial restructuring.

3. Energy structure: Coal is an inefficient source of energy, and its excessive use will reduce energy efficiency. As per Chen and Wang (2010), inefficient energy sources, such as coal, can reduce total energy consumption and improve energy efficiency.

4. Ownership structure: Ru and Si (2015) noted that foreign-owned and private-owned enterprises are more competitive than state-owned enterprises, and also that the former have had more success in improving energy efficiency. They proposed encouraging state-owned enterprises to reform their concepts and technologies to improve their energy efficiency. In this study, the ownership structure of state-owned and state-controlled enterprises is expressed as the proportion of gross output value and gross industrial output value.

5. Capital deepening: As technology intensity may have an indirect effect on energy efficiency, Tao and Qi (2010) argued that capital deepening reflects the degree of technology-intensive use of the economy, while using labor-capital stock (K/L). Capital deepening, this article for reference, and made a logarithmic treatment.

6. Dependence on foreign direct investment (FDI): FDI is an important source of technological progress. It introduces relatively advanced energy technologies, and energy efficiency can be improved through technology spillovers to domestic-funded enterprises (Wang et al., 2011). The relevant variable used in the model is the proportion of FDI to PGDP.

7. Trade dependence or foreign trade coefficient: The degree of dependence on trade can reflect China’s dependence on the international market and the extent to which its economy has opened up to the outside world. In fact, China is the world’s factory and thus has been an exporter of net (implied or implicit) energy. If the international division of labor and trade structure is irrational, China’s energy efficiency will be affected considerably. The relevant variables used in the model analysis are expressed as the shares of total imports and exports in GDP.

**Spatial Weight Matrix and Model Selection**

We constructed six spatial weight matrices, as follows. (a) Based on the adjacent relationships between provinces in China, we constructed the binary adjacency weight matrix (W1) of 29 provinces and cities. (b) We created a spatial weight matrix based on the latitude and longitude of China’s provincial capital cities (W2). (c) The economic weight matrix (W3) was constructed according to the per capita GDP data of 29 provinces in China from 1990 to 2016. (d) We constructed the economic distance matrix (W4). (e) The composite space weight matrix (W5) of the economy and distance was constructed using the multiplicative method of the large circle spatial distance weight matrix and the economic weight matrix. (f) The weight matrix of the large circle spatial distance and the linear of the economic weight matrix. The composite spatial weight matrix (W6) of economy and distance was constructed.

Is there any spatial effect of energy efficiency under the constraint of resources and environment, and which dependency relationship of spatial effect is related to which one or several kinds of spatial weight matrix? To address these questions, it is necessary to pay special attention to the fact that this method has been observed to be inconsistent with the practice of spatial econometrics analysis by a large number of studies based in China. Based on the simulation analysis, we find that choosing an unreasonable spatial weight matrix causes considerable interference in further analysis; thus, we identified this as the first problem that needed solving. The global spatial autocorrelation M1 test was performed using the spatial weight matrix. The test results are shown in Table 3.

Table 3 shows that only two spatial weight matrices, W2 and W6, are highly significant at the 1% level, that is, a spatial effect exists. The spatial weights matrices W1 and W2 (based on the adjacency and distance) do not have significant
spatial effects. The following matrices were needed to build an appropriate measurement model based on W2 and W6, that is, additional model selection analysis was needed. Based on the theory of spatial econometric model selection, we carried out the MI test on two different spatial weight matrices (W2 and W6) and the results obtained are shown in Table 4.

Table 4 shows which matrix is a better selection: W2 or W6. The results for LM2, LM3, LM4, and LM6 are significant at 10%, whereas those for LM1 and LM5 are not significant. Thus, we can conclude that the spatial econometric model should be of either the spatial lag or the generalized spatial form, and that we cannot choose the SEM and the spatial error component model for the analysis. However, two uncertainties remain: the choice of the SAR or SAC, namely, the forms of W2 and W6. It is important to understand whether W2 or W6 is the optimal model, or whether they may both be added to the generalized spatial model. Whereas the results from the LM test cannot give the exact conclusion, the MCMC method in space measurement model selection theory can provide a good solution. The posterior probabilities of the SAR models using W2 and W6 are 0.146 and 0.182, respectively. The posterior probabilities of the generalized spatial measurement model with W6 as the spatial lag weight matrix, and W2 as the spatial error weight matrix, is the largest. Thus, we chose this model for the empirical analysis.

Model Estimation and Analysis

Based on the spatial heterogeneity of energy efficiency under resource and environmental constraints, and the above points, we considered a spatial variance-based generalized spatial econometric Model 1 for judging the spatial weight matrix, model selection, and model robustness.

\[
y = \rho W_y y + \beta_1 PGDP + \beta_2 IS + \beta_3 ES + \beta_4 OS + \beta_5 KL + \beta_6 FDI + \beta_7 IE + \mu, \\
\mu = \lambda W_2 \mu + \epsilon, \epsilon \sim N(0, \sigma^2 V), V = \text{diag} (\lambda_1, \lambda_2, \ldots, \lambda_n). 
\]  

Model 1 is estimated by using the MCMC estimation method with unknown heteroscedasticity, as introduced by Tao and Yang (2014), and the results are shown in Table 5.

Table 5 shows that the fitting effect of the whole model is better, with the \( R^2 \) values being .921 and .896, respectively. The spatial autocorrelation coefficient and the autocorrelation coefficient of the model are significantly different from each other at the 1% level, that is, there is an obvious spatial effect. The energy efficiency of a province will be indirectly affected by the energy efficiency of neighboring provinces and cities, and if this effect is not taken into account, the entire model will have an estimation bias. Whereas the per capita GDP energy efficiency is positive, the impact is insignificant. The increase in per capita income may change the structure of people’s energy use, but its impact is not obviously related to the energy structure itself. The regression coefficient of the energy structure indicates that China’s energy structure itself has a direct and significant impact on energy efficiency; moreover, this impact is potentially negative. This implies
Table 5. Estimation Results of Model 1 Based on the MCMC Method.

| Variable | Coefficient | Asymptotic t-statistic | p value |
|----------|-------------|------------------------|---------|
| PGDP     | 0.0213      | 1.023                  | .348    |
| IS       | 0.839       | 4.21***                | .000    |
| ES       | -0.316      | -3.86***               | .000    |
| OS       | -0.428      | -4.86***               | .000    |
| KL       | 0.008       | 0.737                  | .161    |
| FDI      | 2.281       | 2.988***               | .003    |
| IE       | -1.631      | -2.832***              | .005    |
| ρ        | 0.931       | 12.038***              | .000    |
| λ        | -7.743      | -101.22***             | .000    |
| $R^2$    | .921        |                        |         |
| Adjusted $R^2$ | .896      |                        |         |
| Log likelihood | 88.863   |                        |         |

Note. MCMC method can only be asymptotically t-statistics. PGDP = level of economic development; IS = industrial structure; ES = energy structure; OS = ownership structure; KL = capital deepening; FDI = foreign direct investment; IE = trade dependence.

"***" indicates significance at the 10%, 5%, 1% level.

that considering resource and environmental constraints under the condition of excessive dependence on coal will greatly reduce China’s energy efficiency and coal consumption, and thus, the negative impact cannot be ignored. In addition, ownership structure and trade dependence also have negative effects on energy efficiency. As ownership structure is expressed as the proportion of total output value of state-owned and state-controlled enterprises to gross industrial output of private enterprises, which are more competitive than state-owned enterprises, they have a positive impact on improving energy efficiency, which is consistent with most scholars’ conclusions. However, Wang et al. (2011) opposed this idea, perhaps because the regression model of the factors and the chosen variables are different for the energy efficiency measures. Wang et al. (2011) used an ordinary Tobit model, which did not consider space effects. The estimation was erroneous and the impact of trade dependence on energy efficiency was not considered. The increase in the shares of total imports and exports in China’s GDP also have a negative impact on China’s energy efficiency. This suggests that as a world factory, China needs to improve its division of labor and trade structure on an international scale. Like many developing countries, industries in China too are facing issues in controlling the environmental pollution caused by the export of resource-consuming products, that is, the “pollution haven” hypothesis certainly applies to China. The impact of the industrial structure variables on energy efficiency is positive and highly significant. It can be seen that the increase in the proportion of the service industry is conducive to the overall improvement in energy efficiency because it is a low-energy-consumption industry. China is undergoing rapid urbanization and industrialization. Given its huge chemical industry and rising energy consumption, the country’s carbon intensity is increasing, leading to a decline in its energy efficiency. The dependence of foreign capital on energy efficiency is also positive and highly significant, which shows that foreign-funded enterprises will adopt more advanced energy technologies and have positive spillover effects on domestic enterprises.

Generally, the increase in per capita income may change the structure of people’s use of energy. This change in the structure of energy use itself shows a positive effect on the improvement of energy efficiency, but this effect is not significant. The reason may be that the direct impact of increased income is to bring people the convenience of energy use and does not directly affect the efficiency of energy use. In fact, with the rise of living standards, people who originally relied on cheap energy and will be switching to a more expensive but more convenient and clean energy source will not directly consider whether it will help increase energy efficiency. This model concludes that the impact of capital deepening represented by the stock of labor capital is not significant for energy efficiency. The reason may be that this variable reflects the intensity of technology in the entire economy, and it is closely related to the technical use of the entire society. However, the impact on energy efficiency alone may not have a more direct impact.

Main Findings and Policy Recommendations

The DEA model is based on the principle of optimization and cannot be analyzed by the various tests (such as statistical analysis) typically used to designate the effectiveness of such a model. Therefore, the results of the different methods vary when we try to measure TFEE. Use of the DEA model requires careful selection. In addition, we should consider resource and environmental constraints while measuring TFEE to ensure that the results are more in line with China’s actual situation. In addition, the influence of the space effect should be taken into account when analyzing the factors affecting energy efficiency at the provincial level. Neglecting the influence of the spatial effect will lead to biased estimations. Notably, when considering the spatial effect, we need to choose the appropriate spatial weight matrix and spatial econometric model according to the theory and method of spatial measurement. We also need to use a reasonable model estimation method. Only with the proper integration of these processes can we create a complete framework for TFEE analysis.

According to the estimated total TFEE under resource and environmental constraints, the current trend of TFEE in China is not optimistic and requires urgent attention. Accordingly, we make the following policy recommendations.

1. The TFEE differs significantly by province, and hence, the policy formulation and implementation
should be comprehensive, considering the characteristics of the provincial region. The conventional practice of “one size fits all” should not apply. Regions with low total energy efficiency should be provided incentives and should be encouraged to learn from the effective regulatory approaches of regions with high total energy efficiency. This is crucial as it is not possible to improve per capita GDP as a direct means of improving total energy efficiency. Doing so encourages some local governments to prioritize investments in heavy industry instead of reducing the TFEE.

2. Reasonable adjustment of industrial structure can significantly improve the TFEE. This should be based on the stage of local economic development and its resource environment. With regard to the regional industrial structure’s energy saving and production, inefficient industries (i.e., those with high energy consumption and high pollution levels) should continue to be phased out or effectively controlled. For regions with high resource endowments, the government should focus on technological transformation and upgrading of these industries to gradually optimize the provinces’ industrial structure and achieve coordinated development with energy consumption and environmental improvement. In particular, the government should enhance the energy-efficient development of new industries and move toward a new economic growth paradigm for the regional economy as a whole.

3. Too much reliance on coal-based (highly polluting) energy is the main reason for the poor total energy efficiency in China. However, the coal-dominated energy consumption structure is long term and it is quite difficult to change it at short notice. Thus, there should be a gradual reduction in this dependence by encouraging the use of advanced clean/renewable energy technologies and efficient energy usage. Thus, the supply of renewable energy should be improved.

4. State-owned and state-controlled enterprises should focus on improving the TFEE level. Moreover, the government should encourage state-owned enterprises to consider property rights restructuring, absorb advanced technologies used by private and foreign enterprises, and implement ideas to encourage the use of clean energy, energy conservation, and cleaner production. Doing so would cultivate awareness about the concurrent need for energy efficiency and development within the enterprise. The government should therefore intensify reforms at state-owned enterprises from all aspects, including the systemic, administrative, and cultural.

5. With the opening up of its economy to the outside world, China has attracted huge foreign investments. China has also enjoyed the spillover effects of international technology, which have played an important role in enhancing its total energy efficiency. Some developed countries, such as Europe and the United States, focus on energy efficiency and environmental awareness, whereas others, such as Hong Kong, Macao, and Taiwan focus on business efficiency in foreign investment as their own R&D investments and level of technology used are low. Thus, China cannot afford to ignore the pollution problems caused by the use of inefficient energy sources; it should absorb the advanced technologies used by developed countries, cultivate independent innovation, and build a certain constraint mechanism.

6. Unreasonable international division of the labor and trade structure will pose challenges to improving China’s TFEE. It is thus necessary to avoid the large-scale transfer of pollution-intensive industries from the international stage to China by controlling the exchange of resources and energy-intensive products through the import-export trade.

Declaration of Conflicting Interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This article is a phased result of the research on the driving mechanism, mode selection, and path of upgrading China’s advanced manufacturing base from the perspective of the youth project of the Ministry of Education: Industrial collaborative innovation (19YJC630010).

References
Banker, R. D., Charnes, A., Cooper, W. W., Swarts, J., & Thomas, D. (1989). An introduction to data envelopment analysis with some of its models and their users. Research in Government and Nonprofit Accounting, 5, 125–163.

Chen, Y.-g. (2009). Reconstructing the mathematical process of spatial autocorrelation based on the Moran statistic. Geographical Research, 28(6), 1449–1463.

Chen, Y., & Wang, H. (2010). The impact of FDI on inter-provincial industrial energy efficiency. Contemporary Finance and Economics, 308(7), 99–106.

Chen, Z., Li, J., Zhao, W., Yuan, X.-C., & Yang, G.-l. (2019). Undesirable and desirable energy congestion measurements for regional coal-fired power generation industry in China. Energy Policy, 125, 122–134.

Cheng, G. (2014). Data envelopment analysis method and Max DEA software. Intellectual Property Press.

Chung, Y. H., Fare, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. Journal of Environmental Management, 51(3), 229–240.

Cook, W. D., Liang, L., Zha, Y., & Zhu, J. (2009). A modified super-efficiency DEA model for infeasibility. Journal of the Operational Research Society, 60, 276–281.

Hang, Y., Sun, J. S., Wang, Q. W., & Wang, Y. Z. (2015). Measuring energy inefficiency with undesirable outputs and technology heterogeneity in Chinese cities. Economic Modelling, 49, 46–52.
Honma, S., & Hu, J. L. (2009). Total-factor energy productivity growth of regions in Japan. *Energy Policy*, 37, 3941–3950.

Hu, J. L., & Chang, T. P. (2009). Total-factor energy productivity growth of regions in China [Working paper]. National Chiao Tung University.

Hu, J. L., & Wang, S. C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy*, 34(17), 3206–3217.

International Energy Agency. (2010). *Shaping a secure and sustainable energy future for all*. https://www.iea.org/

Kostov, P. (2010). Model boosting for spatial weighting matrix selection in spatial lag models. *Environment and Planning B: Planning and Design*, 37(3), 533–549.

Pang, R. Z., Deng, Z. Q., & Hu, J. L. (2015). Clean energy use and total-factor efficiencies: An international comparison. *Renewable & Sustainable Energy Reviews*, 52, 1158–1171.

Ru, L., & Si, W. (2015). Ownership structure and enterprise energy efficiency–an empirical study based on sugar industry. *Journal of Dalian University of Technology* (Social Science Edition). Online Edition.

Shan, H. (2008). Re-estimation of China’s capital stock K. 1952–2006. *Quantitative Economic Technical Economic Research*, 10, 18–32.

Shephard, R. W. (1953). *Cost and production functions*. Princeton University Press.

Shephard, R. W. (1970). *Theory of production functions*. Princeton University Press.

Tao, C., & Qi, Y. (2010). Spatial difference of total factor productivity in China and analysis of its causes. *Quantitative Economic Technology and Economic Research*, 1, 19–32.

Tao, C., & Yang, H. (2014). Efficient estimation of unknown heteroscedastic generalized spaces model. *Quantitative Technology and Economic Research*, 31(9), 107–123.

Tone, K., & Tsutsui, M. (2010). An Epsilon-based measure of efficiency in DEA-A third pole of technical efficiency. *European Journal of Operational Research*, 207, 1554–1563.

Wang, B., Zhang, J., & Zhang, H. (2011). Empirical research on China’s inter-provincial total factor energy efficiency under environmental constraints. *Economic Review*, 4, 31–43.

Wang, H., Ang, B. W., Wang, Q. W., & Zhou, P. (2017). Measuring energy performance with sectoral heterogeneity: A non-parametric frontier approach. *Energy Economics*, 62, 70–78.

Wang, Q., Zhao, Z., Zhou, P., & Zhou, D. (2013). Energy efficiency and production technology heterogeneity in China: A meta-frontier DEA approach. *Economic Modelling*, 35, 283–289.

Yuan, X., Zhang, B., & Yang, W. (2009). Research on China’s total factor energy efficiency based on environmental pollution. *China Industrial Economy*, 002, 76–86.

Zhang, X. P., Cheng, X. M., Yuan, J. H., & Gao, X. J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy*, 39(2), 644–650.

Zhao, H. X., Mu, H. L., Chen, X., & Han, X. (2014). Total-factor energy efficiency and influence factors analysis in regions of China. *Applied Mechanics & Materials*, 672–674, 2158–2164.

Zhu, P., Zhang, Z., & Jiang, G. (2011). FDI and environmental regulation: An empirical study based on the perspective of local decentralization. *Economic Research*, 6, 133–145.