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Sustainable Evolution of China's Regional Energy Efficiency Based on a Weighted SBM Model with Energy Substitutability

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Abstract: The rapid economy expansion in China has substantially increased energy consumption. Under the stringent environmental policy and the requirement of green economy development, the accurate assessment and analysis of energy efficiency is an increasingly significant issue for energy development policy making in China. This study uses the weighted slacks-based model (weighted SBM) considering the energy substitutability to evaluate the regional energy efficiency (EE) in 29 Chinese provinces, from 1991 to 2015, and explores the sustainable evolution characteristics of EE by comparative and convergence analyses from different perspectives. The empirical results show that EE has significant geographic differences. On the one hand, EE increases from the west to the east of China, and its volatility has a rising trend over the period 1991–2015. Only the EE in the eastern area had a stable rising trend, and the EE differences are difficult to reduce in the short term. On the other hand, the economic zones in the south of China, such as Central Bohai, Pearl River Delta, and Yangtze River Delta, have higher EE. We also find a significant EE improvement occurred during the Eleventh and the Twelfth Five-Year plans. By means of the convergence analysis of energy efficiency across different areas and economic zones over different time intervals, it is shown that EE in the southeast coast provinces have a better catching-up effect and adjustment rate toward the efficient frontier, while the western inland provinces are less effective over the period 1991–2005. Further, we empirically find that the industry policies including industry transfer policy promote EE globally, but the regional differences and fluctuations in EE remain serious. Certain policy implications are discussed with regard to sustainable regional development and an effective industry transfer policy.

Keywords: energy efficiency; energy substitutability; weighted SBM; convergence

1. Introduction

In recent decades, there has been great progress in the economic and social development of China. However, China's growth is accompanied by a significant increasing energy consumption due to the large number of energy-intensive industries. Meanwhile, the energy consumption pattern in China is dominated by fossil fuels, which has not changed significantly. As noted by Li and Oberheitmann [1], continually increasing energy consumption will lead to inefficient natural resource utilization and improving energy efficiency is regarded as a key measure for reconciling the conflict between economic growth and energy consumption. Therefore, the accurate analysis of Chinese energy efficiency is a significant issue for making policies that promote energy development and transform the economic growth mode in response to these challenges.

As is well known, energy should be accompanied by labor and capital to produce outputs, so we must employ multiple-factor models to evaluate the energy efficiency of the decision making units (DMUs). As Rao et al. [2] pointed out, the equal weight assumption is often used in the implementation of an efficiency model, so almost all previous studies that assess energy efficiency have paid little attention to the relative importance of different inputs. However, due to the effect of energy scarcity on economic growth, the input indicators especially for the energy input in the actual production process have different levels of importance [3]. Therefore, a main objective of this paper is to evaluate energy efficiency by proposing a new weighted slacks-based measure, in which the weights are determined by a quantitative method based on energy substitutability estimated from the translog production function.

In order to achieve the sustainable development of energy, the Chinese government has carried out a series of energy policies and strategies (e.g., Five-Year plans). However, China's regional development is significantly unbalanced, and the implementation of various policies has been tailored to local conditions, so these policy differences and regional differences may affect regional energy efficiency. The existing research has mainly analyzed the energy efficiency in three areas of China and found high efficiency in the east and low efficiency in the west, but most studies do not conduct an in-depth study on the north–south characteristics of the energy efficiency based on the seven economic zones and ignore the dynamic evolution of regional differences in energy efficiency. Meanwhile, most studies have found an increase in energy efficiency over the sample period and studied the influencing factors, but few studies have compared and analyzed the promotion effects of different energy and industrial policies (e.g., industrial transfer policy) on energy efficiency. In addition, although some existing research has analyzed the catching-up effect of energy efficiency, it has not found consistent evidence. Meanwhile, they ignored the comparisons between different time periods and regional divisions, and other types of convergence characteristics are not considered. Therefore, another contribution of this paper is to provide a more detailed analysis of energy efficiency from different aspects, such as regional divisions, Five-Year energy plans, and industrial transfer policies. We try to capture the convergence characteristics of energy efficiency by using three major convergence concepts: β-convergence, σ-convergence, and λ-convergence; this helps to clarify the regional gaps in the improvement of energy efficiency and allows us to offer practical information for policy makers.

In summary, this paper expands the existing literature through innovation in several aspects. First, this paper provides a new energy efficiency measurement that employs a weighted slacks-based model (SBM) method considering energy substitutability; this method overcomes the shortcomings of the majority of studies on energy efficiency that ignore the relative importance of different input indicators. Second, according to regional divisions of "three areas" and "seven economic zones", this paper investigates the differences in regional energy efficiency. In addition, this paper considers a long span of 25 years, using data from 1991 to 2015; this helps us to understand the change pattern in energy efficiency over different Five-Year plans, and provides empirical evidence on the regional effects caused by different energy and industry policies. Finally, this paper analyzes different convergence characteristics of regional energy efficiency, such as the catching-up effect, the cross-sectional dispersion effect, and the adjustment effect toward the best frontier, according to different regional divisions and time interval divisions. All of these factors and innovations help us better understand the sustainable evolution characteristics of Chinese regional energy efficiency.

The paper is organized as follows. In Section 2, we review the relevant literature. Section 3 introduces the weighted SBM model and economic implications of the weight, and it then proposes the method for quantifying input weights based on energy substitutability. Then, the econometric model for capturing the efficient sustainable evolution characteristics by convergence analysis is presented. Section 4 offers the estimation process and results for energy substitutability weights in the SBM model, and it analyzes the evolution trend, differences in regional and economic zones, and the Five-Year planning policy effects on Chinese regional energy efficiency. Section 5 provides an analysis of the convergence characteristics of energy efficiency in different regions, economic zones, and time periods, and it provides some comparative analysis combined with an energy policy and an industrial transfer policy. In Section 6, we summarize the conclusions and propose some policy implications.

2. Literature Review

Various parametric or nonparametric methods are often employed to measure the energy efficiency, and these evaluating models have different improvements based on real-life requirements. In this section, we review the literature on the most relevant quantitative methods for estimating energy efficiency, and then summarize certain analytical perspectives and techniques related to our research.

The SFA (Stochastic Frontier Analysis) model based on linear regression is a primary parametric approach for evaluating energy efficiency [4–6]. However, the approach taken by these studies demonstrates only a single linear relationship from input variable to output variable, which cannot completely capture the changing behavior of energy efficiency. Moreover, one may also encounter difficult problems such as endogeneity [7], residual distribution [8], and heterogeneity [9] in the parameter estimation process. To solve the problems above, the data envelopment analysis (DEA) method developed by Charnes et al. [10] has been widely applied in evaluating the energy efficiency of different regions or countries and monitoring efficiency evolution. As indicated by Liu et al. [11] and Meng et al. [12], a rapid increase in literature is produced by using the DEA models to evaluate the energy and technical efficiency of different DMUs in various situations, e.g., industrial sectors in Wu et al. [13], the construction industry in Feng and Wang [14], the iron and steel industry in Yang et al. [15], the transport industry in Feng and Wang [16], the environmental efficiency in Xu et al. [17], and the Chinese regional energy efficiency in Wang et al. [18]. However, the DEA model treats the internal production process as a “black box” [19] and assumes that it is invariant with respect to DMUs. In addition, during the process of using DEA models, we need to choose the input-oriented type or the output-oriented type, which focuses the process on either reducing the inputs given the outputs or increasing the outputs given the inputs.

The SBM model proposed by Tone [20] optimizes the objective function by finding slacks (input excess or output shortfall), which is different from the DEA (CCR or BCC) model of Charnes et al. [10] and has non-radial and unoriented advantages. Therefore, the SBM model can provide more analysis information than the DEA model on energy inefficiency. In recent years, the SBM model has become popular worldwide for its use in energy efficiency assessment, and many studies have applied SBM models and improved SBM models to examine industrial energy efficiency or regional energy efficiency [2,21–26]. Rao et al. [2] employed the SBM method to investigate the provincial energy efficiency and energy saving potential in China during the period 2000–2009 for the first time. Du et al. [22] constructed a slacks-based measure data envelopment analysis (SBM-DEA) model to analyze the provincial energy efficiency and its driving factors. Cai et al. [25] found great differences in regional energy efficiency among Chinese provinces and analyzed the emission reduction potential based on the hybrid SBM model. Du et al. [26] utilized the super SBM model to analyze the Chinese energy efficiency of different regions divided based on urban agglomeration and found some kind of spatial distribution relationship between energy efficiency and urban agglomeration. Lin and Zhang [27] used a meta-frontier SBM model to evaluate the energy efficiency of the Chinese service sector and found only the eastern region shows an increasing trend in the energy efficiency. Li and Shi [21] and Yang et al. [28] used the improved super SBM model to measure the energy efficiency of Chinese industrial sectors and provinces, respectively. Zhu et al. [29] explored the dynamic evolution of regional energy efficiency in China with an improved multidirectional efficiency analysis and found the comprehensive energy efficiency of different provinces were not highly fluid between different levels. Liu et al. [30] and Cheng et al. [31], respectively, used the DEA-BCC model and meta-frontier method to estimate China’s energy efficiency at the provincial level, and found a considerable difference in energy efficiency among provinces.

However, the literature on energy efficiency measured by SBM models rarely considers the relative importance of different inputs or different outputs, so the research results obtained may be affected by this equal weight assumption. Especially in the current situation of energy scarcity, the input indicators such as labor, investment, and energy obviously have different amounts of importance in the actual production process. Thus, during the process of estimating energy efficiency, we should focus on the relative importance of different inputs. Zhou et al. [32,33] used the weighted SBM method to analyze the environmental efficiency of Chinese industrial sectors, but the energy-input weights were decided by the energy reserve or information entropy method. Xiong et al. [34] constructed a weighted zero-sum game data envelopment analysis (ZSG-DEA) model to study the allocation efficiency of energy consumption. Therefore, in this paper, we propose a new quantitative weighting method based on the translog production function for the SBM model considering energy substitutability among different input indicators.

Currently, the regional characteristics (e.g., geographical location and resource endowment) and macro policy plans (e.g., industrial policy and energy policy) have become increasingly pronounced for regional energy efficiency, especially in coastal and inland areas or special economic zones (SEZ). Therefore, we utilize the convergence technique to obtain a more detailed analysis of such regional differences in energy efficiency. The convergence analysis proposed by Baumol [35] has been deployed commonly in economic growth theory based on total factor productivity (TFP), but it makes some restrictive assumptions about input–output conversion that are difficult to verify [36]. Therefore, convergence analysis based on DEA or SBM models becomes more important from the input–output perspective. Recently, many studies have examined the convergence characteristics of energy efficiency. Li and Lin [37], Zhang et al. [38], and Han et al. [39] measured regional energy efficiency using different methods, but they all examined only the catching-up effect of energy efficiency. Pan et al. [40] tested the club convergence characteristics of regional energy efficiency using the Markov chain method and indicated the relationship between regional energy efficiency and regional characteristics.

On the whole, some shortcomings of previous studies are addressed in this paper. First, although there are various studies analyzing regional energy efficiency, most of them pay little attention to the relative importance of different input indicators, and there is also no study that uses a quantitative method to determine the importance of input indicators. Second, in the literature on the empirical analysis of energy efficiency, most studies ignore the efficiency differences in China's seven economic zones, and they do not conduct a comparison analysis of the effects of policy on energy efficiency improvements. Third, most of the previous research on the convergence analysis of energy efficiency only explores the catching-up convergence characteristics, and there is no regional study on efficiency convergence characteristics. To solve these problems, this study provides a new weighted slacks-based model for measuring energy efficiency that considers energy substitutability. The empirical study sections of this paper provide the quantitative process used to determine the weights, and it analyzes the sustainable evolution characteristics of regional energy efficiency by comparative and convergence analysis from different perspectives, including regional divisions, Five-Year plan guidance, and industry transfer policy.

3. Methodology

In this section, we provide the economic implication of the improved weighted SBM efficiency model with weights quantified based on energy substitutability, and then state efficiency convergence models for the sustainable evolution analysis of energy efficiency. Figure 1 illustrates the whole research idea of this paper and some key steps.

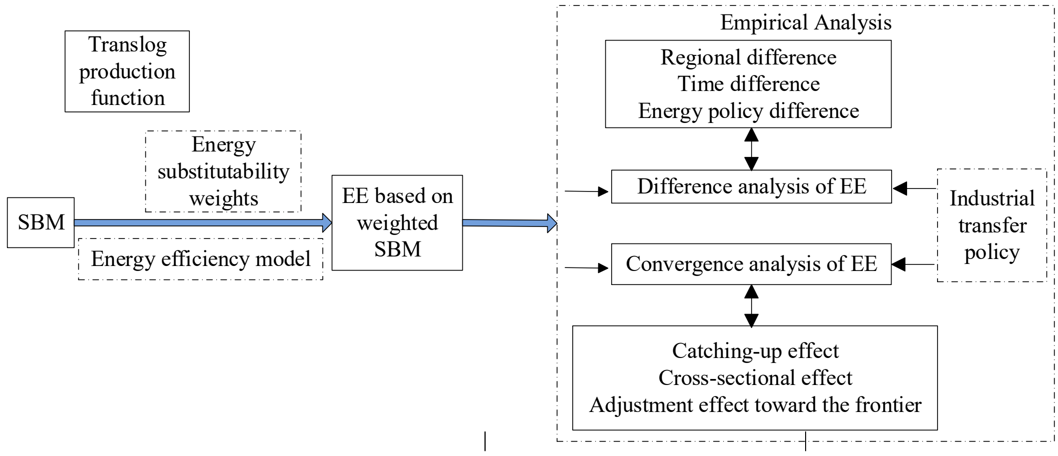

Figure 1. Flowchart of the improved energy efficiency (EE) model and the whole empirical analysis steps.

3.1. The Weighted SBM Model

We assume that a production system has n decision making units (DMUs), and the vector representations of inputs and outputs for each DMU are $x \in R^m, y \in R^s$, where m and s denote the number of indicators for inputs and outputs, respectively. We define the input and output matrices $X, Y(X > 0, Y > 0)$ as follows:

$$X_{m\times n} = [x_1, x_2, \cdots, x_n] \in R^{m\times n},\ Y_{s\times n} = [y_1, y_2, \cdots, y_n] \in R^{s\times n}. \quad (1)$$

Then, under the assumption of strong disposability, the production possibility set P has the following formula:

$$P = \left\{(x, y)\middle| x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\right\}, \quad (2)$$

where $\lambda = (\lambda_1, \lambda_2, \cdots, \lambda_n)$ denotes the intensity vector, and each component of the vector has a corresponding inequality relationship derived in Equation (2). According to the slack-based model (SBM) in Tone [19], if the preference or importance of input/output indicators is different, we impose weights related to the objective function of the SBM model. To evaluate the DMU (x_0, y_0), the optimization function value ρ^* of the following weighted SBM model provides its relative efficiency:

$$[\text{Weighted SBM}]\ \rho^* = \min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{\omega_i^I s_i^I}{x_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s} \frac{\omega_r^O s_r^O}{y_{r0}}}$$

Subject to

$$\begin{gathered} x_{i0} = \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^I (i = 1, 2, \cdots, m) \\ y_{r0} = \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^O (r = 1, 2, \cdots, s) \\ \frac{1}{m}\sum_{i=1}^{m} \omega_i^I = 1, \frac{1}{s}\sum_{r=1}^{s} \omega_r^O = 1, s_i^I \geq 0, s_r^O \geq 0, \lambda_j \geq 0, \omega_i^I \geq 0, \omega_r^O \geq 0 \end{gathered} \quad (3)$$

where the optimal value of ρ^* is the efficiency of DMU_0; ω_i^I and ω_r^O denote the weights of input i and output r, respectively; $s^I = (s_1^I, s_2^I, \cdots, s_m^I)$ and $s^O = (s_1^O, s_2^O, \cdots, s_s^O)$ correspond to the input slack vectors and output slack vectors, respectively. Further, we transfer the above nonlinear programming problem into a linear programming problem using the Charnes–Cooper transformation.

Specifically, set $1+\frac{1}{s}\sum_{r=1}^{s}\frac{\omega_r^O s_r^O}{y_{r0}}=\frac{1}{t}$, and then we can acquire the following linear programming model (L-weighted SBM):

$$[\text{L}-\text{weighted SBM}]\ \tau^*=\min\tau=t-\frac{1}{m}\sum_{i=1}^{m}\frac{\omega_i^I S_i^I}{x_{i0}}$$

Subject to

$$\begin{gathered}1=t+\frac{1}{s}\sum_{r=1}^{s}\frac{\omega_r^O S_r^O}{y_{r0}}\\ x_{i0}t=\sum_{j=1}^{n}\Lambda_j x_{ij}+S_i^I(i=1,2,\cdots,m)\\ y_{r0}t=\sum_{j=1}^{n}\Lambda_j y_{rj}-S_r^O(r=1,2,\cdots,s)\\ \frac{1}{m}\sum_{i=1}^{m}\omega_i^I=1,\frac{1}{s}\sum_{r=1}^{s}\omega_r^O=1,S_i^I\geq 0,S_r^O\geq 0,\Lambda_j\geq 0,\omega_i^I\geq 0,\omega_r^O\geq 0\end{gathered}\tag{4}$$

With the optimized solutions $(t^*,\Lambda^*,S^{I*},S^{O*})$ of the L-weighted SBM model, the optimized solution of the weighted SBM nonlinear equation is $(\lambda^*,s^{I*},s^{O*})=(\Lambda^*/t^*,S^{I*}/t^*,S^{O*}/t^*)$.

Given the weighted SBM efficiency model, we focus on how these input indicator weights affect the efficiency measure of each DMU. Assuming that $E_i^I=\sum_{j=1}^{n}\lambda_j^* x_{ij}/x_{i0}(i=1,2,\cdots,m)$ and $E_r^O=\sum_{j=1}^{n}\lambda_j^* y_{rj}/y_{r0}(r=1,2,\cdots,s)$, if the optimal solution is $(\lambda^*,s^{I*},s^{O*})$, then the object function in Equation (3) has the following formula:

$$\rho^*=[\frac{1}{m}\sum_{i=1}^{m}\omega_i^I E_i^I][\frac{1}{s}\sum_{r=1}^{s}\omega_r^O E_r^O]^{-1}\tag{5}$$

In this paper, we focus on the substitution relationship between different input indicators, particularly for capital and energy, as well as for labor and energy; therefore, we give only the economic implications of the input weights ω_i^I by assuming the output weights $\omega_r^O=1$ in Equation (5) for simplicity. Supposing that the input weights ω_i^I have been identified based on the input substitution relationship, we can then observe the efficiency related to the input weights ω_i^I, E_i^I, and E_i^O from Equation (5). For example, if a higher (or lower) E_i^I happens to be combined with a higher (or lower) input weight ω_i^I for DMU (x_0,y_0), then the efficiency measured by the weighted SBM model could be higher (or lower) than the non-weighted SBM model. Hence, this weighted SBM model could improve the identification ability of the efficiency of different DMUs by considering the relative importance of different input indicators.

Furthermore, how to introduce energy substitutability into the weight calculation of input indicators has become a key procedure of measuring efficiency by the weighted SBM model. This paper utilizes the substitution elasticity between capital, energy, and labor to identify energy substitutability and calculate the input weights. For the calculation of the substitution elasticity coefficient, we refer to the translog production function, which is flexible enough to approximate any production technology [41]. Assuming that a translog production function is twice differentiable and relates output (Y) to some common inputs such as capital (K), labor (L), and energy (E), we present it as follows:

$$\begin{gathered}\ln Y_t=\gamma+\alpha_K\ln K_t+\alpha_L\ln L_t+\alpha_E\ln E_t+\alpha_{KL}\ln K_t\ln L_t+\alpha_{KE}\ln K_t\ln E_t\\ +\alpha_{LE}\ln L_t\ln E_t+\alpha_{KK}(\ln K_t)^2+\alpha_{LL}(\ln L_t)^2+\alpha_{EE}(\ln E_t)^2\end{gathered}\tag{6}$$

where α_* denotes the estimated parameters that correspond to the different input indicators, and γ is a constant. To determine the substitution elasticity, we first calculate the output elasticity for capital

$\eta_K = \frac{dY/Y}{dK/K}$, labor $\eta_L = \frac{dY/Y}{dL/L}$, and energy $\eta_E = \frac{dY/Y}{dE/E}$. By simple differential calculations, we acquire the substitution elasticity coefficients for capital-energy σ_{KE} and labor-energy σ_{LE} as follows:

$$\sigma_{KE} = \left[1 + \left[-\alpha_{KE} + \frac{\eta_K}{\eta_E}\alpha_{EE}\right](-\eta_K + \eta_E)^{-1}\right]^{-1}, \sigma_{LE} = \left[1 + \left[-\alpha_{LE} + \frac{\eta_L}{\eta_E}\alpha_{EE}\right](-\eta_L + \eta_E)^{-1}\right]^{-1} \quad (7)$$

Based on the substitution elasticity, we consider the impact of different inputs on integrated efficiency from the weighted SBM model. Usually, the stronger the substitutability, the weaker the relative importance. Therefore, the input weights of capital, labor, and energy can be constructed in the following formula:

$$\omega_K : \omega_E : \omega_L = \sigma_{KE} : 1 : \sigma_{LE}, \quad (8)$$

where ω_K, ω_E, and ω_L represent the weights related to capital, energy, and labor.

3.2. Modeling the Sustainable Evolution Based on Efficiency Convergence Analysis

To investigate the sustainable evolution characteristics of regional energy efficiency in China, we utilized popular efficiency convergence analysis methods such as $\beta-$convergence, $\sigma-$convergence, and $\lambda-$convergence [42,43].

(1) $\beta-$convergence can measure the catching-up effect, which is inferred by the following regression model:

$$\Delta y_{i,t} = \alpha + \beta \ln(y_{i,t-1}) + \rho\Delta y_{i,t-1} + \varepsilon_{i,t}, i = 1,2,\cdots,n, t = 1,2,\cdots,M, \quad (9)$$

where $y_{i,t}$ indicates the i-th regional efficiency at time t and $\Delta y_{i,t} = \ln(y_{i,t}) - \ln(y_{i,t-1})$. A significant $\beta(<0)$ means there is a catching-up effect that is enhanced as the absolute value of β increases.

(2) $\sigma-$convergence can measure the cross-sectional dispersion effect, which is inferred by the following regression model:

$$\Delta E_{i,t} = \alpha + \sigma E_{i,t-1} + \rho\Delta E_{i,t-1} + \varepsilon_{i,t}, i = 1,2,\cdots,n, t = 1,2,\cdots,M, \quad (10)$$

where $\overline{y}_t$ denotes the average efficiency at time t, and $E_{i,t} = \ln(y_{i,t}) - \ln(\overline{y}_t)$, $\Delta E_{i,t} = E_{i,t} - E_{i,t-1}$. A significant $\sigma(<0)$ means there is a cross-sectional dispersion effect that is enhanced as the absolute value of σ increases.

(3) $\lambda-$convergence can measure the adjustment effect toward the best frontier, so we infer the adjustment mechanisms by running the following regression model:

$$\ln(y_{i,t}) = \lambda \ln(y_{i,t-1}) + \varepsilon_{i,t}, i = 1,2,\cdots,n; t = 1,2,\cdots,M, \quad (11)$$

where $1-\lambda$ could be regarded as an adjustment parameter for measuring the adjustment effect toward the best frontier, and a negative value of $1-\lambda$ means the persistence of inefficiency.

4. Empirical Analysis of Regional Energy Efficiency in China

4.1. Modeling the Sustainable Evolution Based on Efficiency Convergence Analysis

In this paper, we used the annual time series data of input and output indicators during the period 1978–2015 to measure energy substitutability by means of the translog production function, and all of this data was collected from the Wind database. We considered capital (K), labor (L), and energy (E) as the input indicators. We denoted the annual Chinese capital stock based on the perpetual inventory method, the annual Chinese employed persons' number, and annual total consumed energy as inputs K_t, L_t, and E_t, respectively. For the output indicator Y_t, we used the annual Chinese gross domestic product (GDP), which is obtained by converting current prices into constant prices based on the GDP implicit price deflator. To calculate the energy substitutability weights, we first obtained the coefficient estimators using Equation (6). However, coefficient estimation for this linear regression model relies on the independence of the variables. Therefore, we first gauged whether or not there is multicollinearity among the input indicators, as shown in Tables 1 and 2.

Table 1. Pearson correlation coefficients between variables in the translog production function.

	K_t	L_t	E_t	$K_t{\cdot}L_t$	$K_t{\cdot}E_t$	$L_t{\cdot}E_t$	$K_t{\cdot}K_t$	$L_t{\cdot}L_t$	$E_t{\cdot}E_t$
K_t	1.0000								
L_t	0.6097	1.0000							
E_t	0.9286	0.7775	1.0000						
$K_t \cdot L_t$	0.9999	0.6047	0.9262	1.0000					
$K_t \cdot E_t$	0.9943	0.5338	0.8876	0.9949	1.0000				
$L_t \cdot E_t$	0.9249	0.7957	0.9994	0.9224	0.8821	1.0000			
$K_t \cdot K_t$	0.9535	0.4364	0.7800	0.9553	0.9752	0.7749	1.0000		
$L_t \cdot L_t$	0.6440	0.9976	0.8089	0.6391	0.5684	0.8264	0.4676	1.0000	
$E_t \cdot E_t$	0.9705	0.6672	0.9823	0.9692	0.9478	0.9778	0.8581	0.7031	1.0000

Note: All of the Pearson correlation coefficients are significant at the 1% significance level.

Table 2. Multicollinearity diagnostics results of the variables in the translog production function.

Variables	Tolerance	VIF	Variables	Tolerance	VIF	Variables	Tolerance	VIF
LnK	0.002	>100	LnK × LnL	<0.001	>100	LnK × LnK	0.001	>100
LnL	0.064	16	LnK × LnE	<0.001	>100	LnL × LnL	<0.002	>100
LnE	<0.001	>100	LnL × LnE	<0.001	>100	LnE × LnE	0.015	67

From the correlation testing results shown in Table 1, we found some evidence of multicollinearity among the input indicators, especially for the cross terms among capital, labor, and energy. This means that it is not feasible to find the parameter estimators of the translog production function using the OLS (Ordinary Least Square) method. The multicollinearity diagnostic results based on VIF(Variance Inflation Factor) are presented in Table 2.

The larger VIF in Table 2 shows that there is significant multicollinearity between independent variables in the translog production function, which will cause the covariance matrix of the OLS estimators to contain some large values and the parameter estimators to be inefficient. Therefore, we used a coefficient estimation method that employs ridge regression [44] to handle multicollinearity in the following section. For the coefficient estimation of the translog production function using ridge regression, a key procedure is determining the ridge parameter k. We first attempted to estimate the ridge regression for different values of k, and the optimal value of k depends on whether the estimated coefficients have achieved stability; for details see Figure 2.

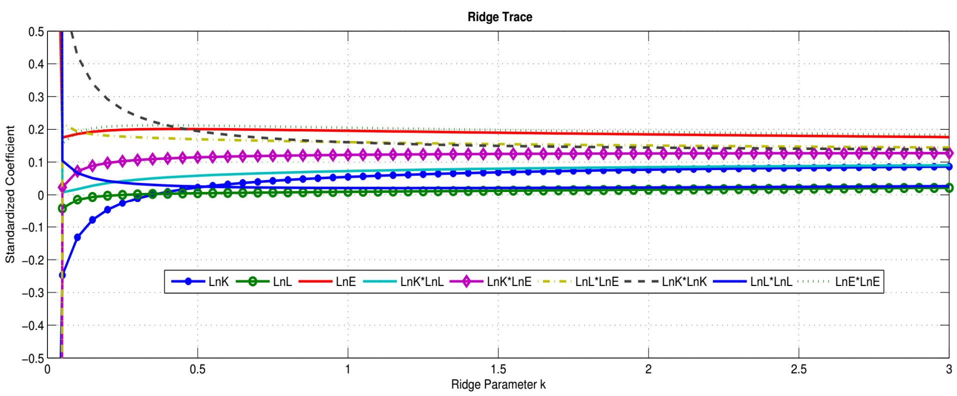

Figure 2. Ridge trace curves of coefficient estimators in the translog production function.

As shown in Figure 2, the ridge trace curves gradually achieved stability. Hence, we chose the ridge parameter $k = 2.5$, and the corresponding parameter estimators of the translog production function are presented in Table 3.

Table 3. Estimation results of the translog production function based on ridge regression.

Variable	Standardized Coeff.	Coeff.	t-Statistic	p-Value	VIF
lnK_t	0.0890	0.0539 *	1.8323	0.0776	0.0149
lnL_t	0.0241	0.1119	0.5628	0.5781	0.0216
lnE_t	0.1727	0.2667 ***	3.6613	0.0010	0.0148
$lnK_t \cdot lnL_t$	0.0921	0.0046 *	1.8666	0.0725	0.0093
$lnK_t \cdot lnE_t$	0.1271	0.0049 **	2.5613	0.0161	0.0051
$lnL_t \cdot lnE_t$	0.1421	0.0150 ***	2.8777	0.0076	0.0080
$lnK_t \cdot lnK_t$	0.1367	0.0041 ***	2.7923	0.0093	0.0102
$lnL_t \cdot lnL_t$	0.0286	0.0061	0.6669	0.5103	0.0215
$lnE_t \cdot lnE_t$	0.1792	0.0116 ***	3.8533	0.0006	0.0165

Note: The values in the second column are the standardized coefficient estimators computed after centering and scaling all variables Y and X into $\widetilde{Y}$ and $\widetilde{X}$, while the values in column Coeff. are the estimation results without centering and scaling. The notation VIF is the variance inflation factor, which is computed from the diagonal elements of the matrix $(\widetilde{X}'\widetilde{X}+kI)^{-1}\widetilde{X}'\widetilde{X}(\widetilde{X}'\widetilde{X}+kI)^{-1}$. The constant of the regression model between X and Y is -0.9757 and the R^2 is 0.9921. The values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Based on the estimation results of Equation (6) in Table 3, the input weights of capital, labor, and energy constructed from the substitution elasticity by Equation (8) are:

$$\omega_K : \omega_E : \omega_L = 0.3266{:}0.3589{:}0.3145 \tag{12}$$

4.2. The Input–Output Data for Regional Energy Efficiency and Regional Divisions in Mainland China

This paper investigates Chinese regional energy efficiency by employing panel data from twenty-nine Chinese municipalities, autonomous regions, and provinces from 1991 to 2015. The data sample does not consider Tibet because so much data is missing; also, we combined the data from Sichuan and Chongqing to maintain a consistent statistical scope. The entire sample period covers different stages of China's development (i.e., the Eighth Five-Year plan, Ninth Five-Year plan, Tenth Five-Year plan, Eleventh Five-Year plan, and Twelfth Five-Year plan), which is convenient for discussing the relationship between energy efficiency and relevant energy or industry policies. For input indicators in the efficiency models, we considered capital, labor, and energy. We chose the provincial capital stock in each year as a proxy for the capital input, the number of provincial employed persons in each year as a proxy for the labor force input, and the amount of provincial energy consumption in each year as a proxy for the energy input. We used the provincial GDP in each year as the final output indicator. We used the perpetual inventory method to calculate the capital stock. Compared with the existing research literature on regional energy efficiency, the sample period of 1991–2015 in this paper is longer, which covers five Five-Year plan development periods in China. During this period, China's energy development has undergone tremendous changes, and energy development policy has undergone a dramatic shift from extensive energy consumption to intensive low-carbon green environmental protection. Therefore, with the help of the study on energy efficiency in this sample period, this paper can analyze the coordination between energy efficiency and energy-industrial policies and clarify the policy factors that lead to the differences in energy efficiency. All of this annual time series data comes from the China statistical Yearbook [45] in the Wind database.

Based on geographical location characteristics, we divided China into three areas: eastern, central, and western areas. From the three areas' divisions in Table 4, we see that the eastern area contains three municipalities and eight coastal provinces located mainly in the Yellow River and Yangtze River Delta areas, while the central area contains eight inland provinces. Obviously, the eastern area and central area have numerous differences in industry, resources, and economies. In addition, although the western area covers a large portion of China, this region is relatively underdeveloped for geographical reasons.

Table 4. The regional divisions in mainland China.

	Region Name (Notation)	The Provinces in the Corresponding Division Region
	Eastern area (E)	Liaoning, Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Three Areas	Central area (C)	Jilin, Heilongjiang, Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan
	Western area (W)	Inner Mongolia, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Xinjiang, Sichuan, Qinghai, Ningxia
	Central Bohai (CB)	Beijing, Tianjin, Hebei, Shandong
	Yangtze River Delta (CD)	Shanghai, Jiangsu, Zhejiang
	Pearl River Delta (PD)	Fujian, Guangdong, Hainan
Seven Economic Zones	Northeast (N)	Liaoning, Jilin, Heilongjiang
	Central Provinces (CP)	Anhui, Jiangxi, Henan, Hubei, Hunan, Shanxi
	Great Southwest (GS)	Guangxi, Guizhou, Yunnan, Sichuan
	Great Northwest (GN)	Shaanxi, Gansu, Xinjiang, Inner Mongolia, Qinghai, Ningxia

The division of the three areas reflects differences from the perspective of regional functions, but there are also large differences among the three areas in economic development, energy endowment, and industrial structure. For example, there are industrial structural differences like "North Heavy and South Light" and energy endowment differences like "North Coal and South Water". Therefore, a more detailed division of mainland China is necessary for a robust energy efficiency analysis. As pointed out in the Twelfth Five-Year plan, different economic zones may adjust the implemented policies to promote economic development, so an energy efficiency analysis based on economic zones will help to clarify the effect of the various relevant industrial policies. According to economic characteristics, we divided China into seven economic zones, as shown in Table 4.

4.3. Provincial Energy Efficiency Results and Tendency Analysis

Based on the weighted SBM methodology that considers energy substitution that we proposed in Section 3, we present the corresponding energy efficiency results and tendency analysis across different years and across different provinces in China; for details, see Table 5.

Table 5. Summary results of provincial energy efficiency in China.

Panel A: Energy Efficiency Across Years								
Year	**Mean**	**Std. dev.**	**Year**	**Mean**	**Std. dev.**	**Year**	**Mean**	**Std. dev.**
1991	0.4776	0.2144	2000	0.3807	0.0758	2009	0.3675	0.1305
1992	0.3602	0.0915	2001	0.3817	0.0857	2010	0.3982	0.1433
1993	0.3020	0.0491	2002	0.3739	0.0895	2011	0.4257	0.1561
1994	0.3194	0.0512	2003	0.3547	0.0874	2012	0.4340	0.1719
1995	0.3488	0.0598	2004	0.3581	0.0925	2013	0.4475	0.1784
1996	0.3804	0.1003	2005	0.3578	0.0985	2014	0.4534	0.1817
1997	0.4191	0.1394	2006	0.3589	0.1085	2015	0.4628	0.1902
1998	0.3805	0.0934	2007	0.3707	0.1159	-	-	-
1999	0.3832	0.0807	2008	0.4273	0.1941	Average	0.3890	0.0843
Panel B: Energy Efficiency Across Provinces								
Provinces	**Mean**	**Std. dev.**	**Provinces**	**Mean**	**Std. dev.**	**Provinces**	**Mean**	**Std. dev.**
Beijing	0.5195	0.2358	Zhejiang	0.4513	0.0883	Hainan	0.3866	0.0459
Tianjin	0.4609	0.1417	Anhui	0.3544	0.0540	Sichuan	0.3442	0.0653
Hebei	0.3358	0.0355	Fujian	0.4662	0.0438	Guizhou	0.2899	0.0724
Shanxi	0.3196	0.0470	Jiangxi	0.4621	0.1720	Yunnan	0.3363	0.0956
Inner Mongolia	0.3620	0.0789	Shandong	0.4141	0.0491	Shaanxi	0.3482	0.0486
Liaoning	0.3743	0.0554	Henan	0.3660	0.0313	Gansu	0.2901	0.0371
Jilin	0.3709	0.0542	Hubei	0.3851	0.1382	Qinghai	0.2509	0.0325
Heilongjiang	0.4157	0.0558	Hunan	0.4468	0.1593	Ningxia	0.2372	0.0402
Shanghai	0.5865	0.2535	Guangdong	0.5470	0.1542	Xinjiang	0.2931	0.0408
Jiangsu	0.4554	0.0920	Guangxi	0.4101	0.1339	Average	0.3890	0.0442

The summary results for energy efficiency in Panel A of Table 5 indicate that Chinese regional energy efficiency had an upward trend from 1991 to 2015. However, energy efficiency declined to an average level lower than 0.37 during the period 2002–2006, and then it gradually rose again, which is consistent with the findings of Bian et al. [23]. In addition, the standard deviations in Panel A also had a slightly rising trend, which indicates the persistence of the difference in regional energy efficiency. China has gone through different leapfrog development stages during this period 1991–2015, and we will give an in-depth analysis in the following subsections.

The summary results of energy efficiency across the twenty-nine provinces are present in Panel B of Table 5. We found that provinces such as Beijing, Shanghai, and Guangdong had energy efficiency of greater than 0.5, and provinces with energy efficiency of less than 0.3 were Gansu, Qinghai, Guizhou, Ningxia, and Xinjiang, which is similar with the findings on the regional ranking of energy efficiency in Du et al. [22]. Accordingly, there are regional distribution characteristics of differences in energy efficiency among Chinese provinces. The standard deviations of provincial energy efficiency show that provinces such as Beijing, Shanghai, Tianjin, Jiangxi, Hubei, Hunan, Guangdong, and Guangxi had a higher standard deviation. Further, there was an upward trend in energy efficiency in many provinces, such as Beijing, Shanghai, Tianjin, Zhejiang, Jiangsu, and Guangdong, while the uptrend of energy efficiency in other provinces was gentler. Hence, the energy efficiency of different provinces shows different evolution trends. For example, the energy efficiency of Beijing, Shanghai, and Guangdong had an upward trend with high means and high volatilities, which indicates that energy efficiency has significantly and rapidly improved during the years 1991–2015 as compared to other provinces. Although the Chinese government has vigorously promoted the new technology revolution, only a few provinces with superior access to capital and beneficial locations, such as Beijing, Shanghai, and Guangdong, have developed a full implementation of new technology and products. Therefore, the improvement of regional energy efficiency remains unbalanced.

4.4. Energy Efficiency Results and Tendency Analysis of the Three Areas

Based on the division of the three areas, we calculate their energy efficiency from 1991 to 2015, as shown in Table 6.

Table 6. Energy efficiency of three areas from 1991 to 2015.

Three Areas	Years								
	1991	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**
Eastern Area	0.4180	0.3344	0.3002	0.3152	0.3362	0.3668	0.3915	0.4014	0.4150
Central Area	0.5856	0.4059	0.3308	0.3485	0.3960	0.4582	0.5084	0.4228	0.4154
Western Area	0.4566	0.3519	0.2811	0.3007	0.3251	0.3331	0.3779	0.3238	0.3226
Overall Area	0.4868	0.3641	0.3040	0.3215	0.3524	0.3860	0.4259	0.3827	0.3843
Three Areas	**Years**								
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Eastern Area	0.4274	0.4451	0.4476	0.4265	0.4363	0.4445	0.4582	0.4772	0.5333
Central Area	0.3985	0.3901	0.3758	0.3548	0.3521	0.3424	0.3334	0.3361	0.4224
Western Area	0.3151	0.3053	0.2911	0.2757	0.2769	0.2748	0.2702	0.2812	0.3145
Overall Area	0.3803	0.3802	0.3715	0.3523	0.3551	0.3539	0.3539	0.3649	0.4234
Three Areas	**Years**								
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Total Average**	
Eastern Area	0.4871	0.5280	0.5610	0.5783	0.5980	0.6072	0.6234	0.4543	
Central Area	0.3159	0.3417	0.3727	0.3720	0.3850	0.3928	0.3947	0.3901	
Western Area	0.2773	0.3006	0.3192	0.3249	0.3321	0.3326	0.3406	0.3162	
Overall Area	0.3601	0.3901	0.4176	0.4250	0.4384	0.4442	0.4529	0.3869	

Note: The efficiency of overall area is calculated by the average energy efficiency of three areas.

Table 6 indicates that only the energy efficiency of the eastern area had a stable rising trend, while the energy efficiency of other areas remained at a low level for a long time. During the period

1991–2015, the energy efficiency of the western and central areas presents a U-type change trend with a slight decline from 2002 to 2006, which is consistent with the findings on energy efficiency during the period 2000–2009 in Rao et al. [2]. Moreover, the differences in energy efficiency between the eastern area and the midwest (central and western) areas expanded slightly, which further verifies the significantly unbalanced development of regional energy efficiency. This was mainly because the technology gap ratio between the central and western regions and the eastern region has been gradually expanding [31]. Energy efficiency indisputably increased in the east versus the west, which may be due to differences in economy development, industrial structure, and technical and management level [2,22,31]. The eastern area of China has the most rapid economic growth and geographical advantages to seize opportunities for industrial technology transfer from developed regions [18]. Thus, the eastern area has rapidly developed into a focal point for China's high-tech industries, which leads to most service industries and foreign technological investment being located in the eastern region. In the western area, the technology level has long been lower than that of the eastern area, and the western area has also accepted industrial transfer of certain heavy industries from the eastern area, which leads to even worse energy efficiency in the west. In recent years, according to guidance on undertaking industrial transfer in the midwest area, the government has tried to accelerate economic structural adjustment and change development patterns. However, from the tendency analysis of energy efficiency, we found that the energy efficiency differences in the eastern and western areas will be difficult to reduce in the short term, and indeed, they may even grow.

4.5. Energy Efficiency Results and Tendency Analysis of the Seven Economic Zones

As stated above in Section 4.2 on regional divisions, large differences still exist among the seven economic zones in terms of economic development, energy endowment, and industrial structure. Therefore, we further analyzed the energy efficiency characteristics of the seven economic zones during the period 1991–2015 in Table 7.

Table 7. Energy efficiency of seven economic zones from 1991 to 2015.

Economic Zones	Years								
	1991	1992	1993	1994	1995	1996	1997	1998	1999
Central Bohai	0.3990	0.3129	0.2890	0.3033	0.3184	0.3426	0.3511	0.3591	0.3701
Yangtze River Delta	0.4446	0.3490	0.3107	0.3217	0.3235	0.3540	0.3879	0.4044	0.4293
Pearl River Delta	0.4396	0.3518	0.3093	0.3322	0.3726	0.4086	0.4491	0.4523	0.4579
Northeast	0.4102	0.3429	0.3041	0.3371	0.3603	0.4634	0.4537	0.3977	0.4034
Central Provinces	0.6340	0.4238	0.3367	0.3449	0.4038	0.4420	0.5163	0.4331	0.4227
Great Southwest	0.6935	0.4624	0.3368	0.3463	0.3570	0.3625	0.3878	0.3545	0.3598
Great Northwest	0.2986	0.2782	0.2440	0.2702	0.3038	0.3135	0.3712	0.3033	0.2978
Economic Zones	**Years**								
	2000	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Central Bohai	0.3883	0.4118	0.4121	0.3939	0.4137	0.4321	0.4411	0.4642	0.4933
Yangtze River Delta	0.4459	0.4591	0.4580	0.4437	0.4587	0.4738	0.5042	0.5330	0.5651
Pearl River Delta	0.4639	0.4854	0.4958	0.4682	0.4806	0.4721	0.4818	0.4902	0.6200
Northeast	0.4077	0.3995	0.3958	0.3856	0.3691	0.3624	0.3488	0.3478	0.3559
Central Provinces	0.3974	0.3898	0.3723	0.3436	0.3393	0.3293	0.3231	0.3281	0.4417
Great Southwest	0.3547	0.3459	0.3362	0.3151	0.3108	0.2982	0.2689	0.2757	0.3235
Great Northwest	0.2886	0.2782	0.2611	0.2494	0.2543	0.2592	0.2710	0.2849	0.3086
Economic Zones	**Years**								
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**Total Average**	
Central Bohai	0.4741	0.5143	0.5430	0.5607	0.5929	0.6121	0.6209	0.4326	
Yangtze River Delta	0.5678	0.6261	0.6787	0.7121	0.7240	0.7228	0.7459	0.4978	
Pearl River Delta	0.4745	0.5040	0.5210	0.5239	0.5336	0.5363	0.5402	0.4666	
Northeast	0.3374	0.3593	0.4024	0.4022	0.4225	0.4425	0.4620	0.3869	
Central Provinces	0.3084	0.3360	0.3623	0.3633	0.3743	0.3781	0.3812	0.3890	
Great Southwest	0.2593	0.2720	0.3007	0.3060	0.3219	0.3279	0.3505	0.3451	
Great Northwest	0.2893	0.3196	0.3315	0.3375	0.3389	0.3358	0.3340	0.2969	

From Table 7, we can see that the energy efficiency in economic zones such as the Yangtze River Delta, Central Bohai, and the Pearl River Delta had a significant rising trend from 1991 to 2015 and was higher than in other economic zones. The vast majority of provinces in the Yangtze River Delta, Central Bohai, and Pearl River Delta economic zones are located in the southeast coastal areas, which have many technology-intensive industries. Therefore, energy efficiency is constantly being optimized. In addition, the energy efficiency of the Great Northwest economic zone from 1991 to 2015 presented the U-type changing trend, while the energy efficiency of the Northeast, Central Provinces, and Great Southwest economic zones had a slight downward trend. The Northeast, Central Provinces, and Great Southwest economic zones have rich energy resources, so energy-intensive industries have long accounted for a large proportion of economic growth. The backward economy and poor awareness of transforming energy consumption patterns cause their low energy efficiency to persist. On the whole, Chinese regional energy efficiency is characterized by "high in the east and low in the west, high in the south and low in the north". This finding presented the regional differences in energy efficiency more comprehensively than most studies [19,29–31], only considering the regional division of three areas.

4.6. Analysis of Regional Energy Efficiency over Different Five-Year Plans

China's Five-Year plans are vital to the country's economic development, and each plan provides the goal and direction of development for the next five years from all aspects, including the economy, science and technology, energy, ecology, culture, and so on. Therefore, to capture the energy efficiency characteristics over different periods of economic development, we explored the changes in regional energy efficiency during five different Five-Year plans, i.e., from the Eighth Five-Year plan to the Twelfth Five-Year plan. Meanwhile, we explained the reasons for the changes in energy efficiency corresponding to the planning contents of each Five-Year plan. The regional energy efficiency over the different Five-Year planning periods is shown in Table 8.

Table 8. Energy efficiency of each area and economic zone during the five Five-Year plans.

Areas	**1991–1995 Eighth-Five**	**1996–2000 Ninth-Five**	**2001–2005 Tenth-Five**	**2006–2010 Eleventh-Five**	**2011–2015 Twelfth-Five**
Eastern Area	0.3408	0.4004	0.4400	0.4968	0.5936
Central Area	0.4133	0.4407	0.3631	0.3499	0.3834
Western Area	0.3431	0.3345	0.2848	0.2888	0.3299
Overall Area	0.3657	0.3919	0.3626	0.3785	0.4356
Economic zones	**1991–1995 Eighth-Five**	**1996–2000 Ninth-Five**	**2001–2005 Tenth-Five**	**2006–2010 Eleventh-Five**	**2011–2015 Twelfth-Five**
Central Bohai	0.3245	0.3622	0.4127	0.4774	0.5859
Yangtze River Delta	0.3499	0.4043	0.4587	0.5592	0.7167
Pearl River Delta	0.3611	0.4464	0.4804	0.5141	0.5310
Northeast	0.3509	0.4252	0.3825	0.3499	0.4263
Central Provinces	0.4286	0.4423	0.3548	0.3475	0.3718
Great Southwest	0.4392	0.3639	0.3212	0.2799	0.3214
Great Northwest	0.2790	0.3149	0.2605	0.2947	0.3355

Table 8 indicates that the regional energy efficiency presents a U-type during these five Five-Year plans, but different areas have their own characteristics. The energy efficiency of the eastern area maintained a steady upward trend, while the energy efficiency of the central and western areas continued to be low, except during the Eleventh Five-Year and Twelfth Five-Year plans, which may be due to the local government that paid more attention to GDP than energy efficiency and environmental protection in the last 20 years. Moreover, energy efficiency showed a steady upward trend for the Yangtze River Delta, Central Bohai, and Pearl River Delta economic zones, and the increase rates were as high as 81%, 105%, and 47%, respectively. The energy efficiency in the Great Northwest economic zone during these five Five-Year plans presents a U-type, while the energy efficiency in the Northeast, Central Provinces, and Great Southwest economic zones did not improve until the Twelfth Five-Year plan. All of these findings show that the evolutionary trends of Chinese regional energy efficiency are inconsistent between different Five-Year plan periods, but all have an upward trend during the Twelfth Five-Year plan period. The reasons from the perspective of energy planning and industrial policies are as follows.

On the whole, Table 8 shows that regional energy efficiency dropped slightly during the Tenth Five-Year plan and then improved gradually in the Eleventh Five-Year and Twelfth Five-Year periods. This is due to the adjustment of product structure and production standards for entering the WTO (World Trade Organization) [15]. Therefore, the Tenth Five-Year period could be considered a transition period. Second, the Tenth Five-Year period started to emphasize improving energy efficiency. It paid more attention to ecological construction, environmental protection, and sustainable economic and social development, but the focus was inclined to mitigate the contradiction between energy supply and demand. In addition, the trade agreement signed by the Chinese government with the Association of Southeast Asian nations in 2002 focused on solving problems in energy-intensive industries, which affected energy efficiency during this period [46]. Since the Eleventh Five-Year plan, the Chinese government became aware that China's energy efficiency was still far behind, as compared with international levels; therefore, the government proposed to reduce energy consumption by about 20% per unit of GDP during the Eleventh Five-Year period. Third, though the use of clean energy is gradually increasing, and energy processing and conversion technologies made breakthroughs during the Eleventh Five-Year plan, there remain many constraints on improving energy efficiency. The Chinese industrial structure is unsustainable, and energy intensive industries are over-developed at a low level. For example, steel, nonferrous, building materials, and chemical industries have a high proportion of energy consumption. During the Twelfth Five-Year period, China made substantial progress in transforming its growth model, readjusting its industrial structure, and improving its capacity for independent innovation in energy science and technology. Meanwhile, in order to lessen the reliance on traditional fossil fuel energy resources, more provinces have obviously paid attention to the development of clean energy, such as wind energy and solar energy. All of these advances have contributed to the improvement in energy efficiency. Therefore, the energy planning policy and industrial development policy in China are gradually playing a positive role in promoting the sustainable development of the economy and energy efficiency.

5. Convergence Analysis of Chinese Regional Energy Efficiency

To obtain the parameter estimation results for Equation (9) and Equation (10), we considered two estimation methods: the pooled OLS method and the system generalized method of moments (SYS-GMM). The difference between the two approaches is that the pooled OLS method does not include the lagging dependent variable when estimating the convergence rate, while the SYS-GMM method does consider dynamic behavior. For the full sample and regional sample during the period 1991–2015, we present the estimation results using the above two methods in Tables 9 and 10. For the full sample and regional sample in different time intervals (e.g., 1991–2005 and 2006–2015), we present only the estimation results (i.e., Sargan test results), and we considered the dynamic behavior of the dependent variables for simplicity due to the similar analysis process. For details, see Tables 11–13. In the following tables, the values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 9. Estimation results of convergence analysis of energy efficiency for the full sample in the whole period 1991–2015.

Parameter	β-Convergence		σ-Convergence		λ-Convergence
	Pooled OLS	SYS-GMM Two Step	Pooled OLS	SYS-GMM Two Step	SYS-GMM Two Step
α	−0.0615 *** (−3.55)	-	−0.0037 (−0.91)		
β	−0.0705 *** (−4.24)	−0.0697 *** (−15.56)	-	-	-
σ	-	-	−0.0554 *** (−3.74)	−0.4834 *** (−12.55)	-
ρ		−0.2275 *** (−48.34)	-	−0.1215 *** (−22.10)	-
λ	-	-	-	-	0.9440 *** (94.80)
R^2	0.0263	-	0.0206	-	-
Sargan test	-	1.0000	-	1.0000	1.000

Note: The values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 10. Estimation results of convergence analysis of energy efficiency for the regional sample in the whole period 1991–2015.

		β-Convergence			σ-Convergence			λ-Convergence	
		β	Sargan Test	Pooled OLS-R^2	σ	Sargan Test	Pooled OLS-R^2	λ	Sargan Test
Three Areas	Eastern	−0.0456 *** (−3.97)	1.00	-	−0.4541 ** (−2.41)	1.00	-	0.9376 *** (26.72)	1.00
	Central	−0.0325 (−1.20)	1.00	-	−0.4904 *** (−5.35)	1.00	-	0.8858 *** (10.33)	1.00
	Western	−0.0390 ** (−2.47)	1.00	-	−0.3944 *** (−5.49)	1.00	-	0.8981 *** (7.70)	1.00
Seven Economic Zones	Central Bohai	−0.0950 (−1.04)	1.00	-	−0.8983 * (−1.87)	1.00		0.5817 (0.84)	1.00
	Yangtze River Delta	0.0180 (0.02)	1.00	-	1.6322 (0.48)	1.00	-	0.9402 ** (2014)	1.00
	Pearl River Delta	−0.1203 ** (−2.21)	-	0.07	−0.0993 ** (−2.01)	-	0.06	0.7648 ** (2.33)	1.00
	Northeast	−0.2710 *** (−3.03)	-	0.12	−0.3141 *** (−3.49)	-	0.15	−0.1130 (−0.16)	1.00
	Central Provinces	−0.3734 *** (−5.79)		0.20	−0.7471 *** (−3.37)	1.00	-	0.8842 *** (6.16)	1.00
	Great Southwest	−0.3028 *** (−4.71)	-	0.20	−0.1758 *** (−3.95)	-	0.15	1.1225 *** (3.20)	1.00
	Great Northwest	−0.7528 ** (−2.13)	1.00	-	−0.4538 ** (−2.45)	1.00	-	0.8328 *** (5.15)	1.00

Note: The values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 11. Estimation results of convergence analysis of energy efficiency for the full sample in different time intervals.

	β-Convergence		σ-Convergence		λ-Convergence	
	β	Sargan Test	σ	Sargan Test	λ	Sargan Test
1991–2005	−0.0579 *** (−26.45)	1.00	−0.5424 *** (−28.23)	1.00	0.9610 *** (523.41)	1.00
2006–2015	−0.0732 *** (−67.49)	0.9704	−0.7908 *** (−43.64)	0.9742	0.9254 *** (4528.73)	0.9627

Note: The values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 12. Estimation results of convergence analysis of energy efficiency for the three areas in different time intervals.

		β-Convergence		σ-Convergence		λ-Convergence	
		β	Sargan Test	σ	Sargan Test	λ	Sargan Test
1991–2005	Eastern	−0.0366 *** (−4.68)	1.00	−0.1271 ** (−2.28)	1.00	0.9340 *** (98.04)	1.00
	Central	−0.0407 ** (−2.11)	1.00	−0.4872 ** (−8.94)	1.00	0.9944 *** (14.84)	1.00
	Western	−0.0039 (−0.230)	1.00	−0.4227 *** (−4.84)	1.00	0.9892 *** (15.82)	1.00
2006–2015	Eastern	−0.0931 *** (−29.36)	1.00	−0.4098 *** (−4.73)	1.00	0.8917 *** (37.76)	1.00
	Central	−0.0640 *** (−61.40)	1.00	−0.8678 *** (−18.67)	1.00	0.9012 *** (39.65)	1.00
	Western	−0.0580 *** (−67.85)	1.00	−0.5782 *** (−12.33)	1.00	0.9690 *** (56.41)	1.00

Note: The values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

Table 13. Estimation results of convergence analysis of energy efficiency for the seven economic zones in different time intervals.

		β-Convergence		σ-Convergence		λ-Convergence	
		β	Sargan Test	σ	Sargan Test	λ	Sargan Test
1991–2005	Central Bohai	−0.4724 (−1.48)	1.00	−1.3168 (−1.19)	1.00	1.1067 *** (2.78)	1.00
	Yangtze River Delta	−0.2243 (−1.15)	1.00	−0.3208 (−0.60)	1.00	0.6585 (0.99)	1.00
	Pearl River Delta	−0.5165 * (−1.94)	1.00	−4.9890 (−1.15)	1.00	0.5969 * (1.85)	1.00
	Northeast	−0.2602 (−1.24)	1.00	−1.9425 (−1.32)	1.00	−0.1133 (−0.16)	1.00
	Central Provinces	−0.0299 (−1.00)	1.00	−0.5219 *** (−3.67)	1.00	1.0233 *** (10.78)	1.00
	Great Southwest	−0.0250 (−0.47)	1.00	1.0528 (1.38)	1.00	0.6773 * (1.65)	1.00
	Great Northwest	−0.0489 ** (−2.29)	1.00	−0.4949 *** (−2.79)	1.00	0.8001 *** (4.77)	1.00
		β-Convergence		σ-Convergence		λ-Convergence	
		β	Sargan Test	σ	Sargan Test	λ	Sargan Test
2006–2015	Central Bohai	−0.0546 *** (−3.00)	1.00	0.0627 (0.45)	1.00	0.9741 *** (8.62)	1.00
	Yangtze River Delta	−0.3679 ** (−2.00)	1.00	0.4717 (0.22)	1.00	0.9419 *** (10.79)	1.00
	Pearl River Delta	−0.0691 (−0.28)	1.00	−0.2203 *** (−5.82)	1.00	0.9711 *** (2.57)	1.00
	Northeast	−0.0690 (−0.13)	1.00	−0.0313 (−0.02)	1.00	0.6240 (1.56)	1.00
	Central Provinces	−0.0651 *** (−5.90)	1.00	−0.7551 *** (−9.60)	1.00	0.8689 *** (22.25)	1.00
	Great Southwest	−0.0627 *** (−20.31)	1.00	−0.2481 *** (−8.37)	1.00	0.9575 *** (−41.02)	1.00
	Great Northwest	−0.0451 *** (−3.34)	1.00	0.0836 (0.82)	1.00	0.9747 *** (10.37)	1.00

Note: The values in parentheses are the test statistics, and *, **, and *** denote 10%, 5%, and 1% significance levels, respectively.

5.1. Convergence Analysis of Energy Efficiency in the Whole Period

Based on the full sample for the period 1991–2015, we observed the convergence characteristics of regional energy efficiency in China based on $\beta-$convergence, $\sigma-$convergence, and $\lambda-$convergence. The estimation results in Table 9 show that the β and σ convergence rates under the pooled OLS and SYS-GMM methods are all significantly negative at a 1% significance level. This shows that there is a catching-up effect and a narrow cross-sectional dispersion effect in energy efficiency across Chinese provinces, and the catching-up effect from 2000 to 2014 is also verified in Zhang et al. [38], but no catching-up effect in [31]. However, the smaller absolute value of the $\beta-$ coefficient means that the catching-up effect is not sustainable. The σ coefficient shows that the cross-sectional dispersion of energy efficiency is declining, but it does not mean that the energy efficiency characteristics of each region are consistent. The energy efficiency of the eastern area continues to improve but with a gradually decreasing growth rate, while the energy efficiency of the western and central areas remains low for a long time with a slight increase. The significantly positive coefficient $\lambda(\leq 1)$ implies that regional energy efficiency could converge toward the best efficiency frontier. Therefore, Chinese regional energy efficiency is generally improving over the study period.

To explore the regional convergence characteristics of energy efficiency, we estimated the convergence model based on the regional data sample for different areas and economic zones, and the upper panel and bottom panel of Table 10 provide the corresponding estimation results. From the upper panel in Table 10, we see that the eastern and western areas have a significant convergence rate for $\beta-$convergence, while the $\beta-$convergence rate of the central area is negative but not significant, which is almost consistent with the findings in [31]. The greater absolute value of the $\beta-$convergence rate shows that the energy efficiency of the eastern area presents a stronger catching-up effect, which verifies that energy efficiency has significantly been improved based on its upward trend in Section 4.4. For the $\sigma-$convergence and $\lambda-$convergence, we found significant convergence characteristics in the three areas. The high $\sigma-$convergence rate and low $\lambda-$convergence rate in the central area indicate that the energy efficiency of the central area has converged toward a better average level. The $\lambda-$convergence rates of the central and western areas mean that the energy efficiency of these two areas has similar upward evolution characteristics, which is consistent with the results in Section 4.4.

From the bottom panel in Table 10, we found first that the $\beta-$ coefficients are all significantly negative, except for the Yangtze River Delta and Central Bohai economic zones, as determined by the pooled OLS method or the SYS-GMM method, and that there is a greater catching-up effect for the Great Northwest economic zone. Second, the Central Provinces economic zone has a more significant and faster convergence effect for reducing the dispersion of energy efficiency. Third, the significant λ coefficients indicate that the energy efficiency of most of the economic zones (except for the Northeast, Central Bohai, and Great Southwest) converges toward the efficient frontier, while the λ coefficient for the Great Southwest economic zone is greater than 1, indicating the persistence of inefficiency. For the Central Bohai economic zone, the energy efficiency of different provinces shows large differences; for example, Hebei and Shandong provinces do not demonstrate a sustainable improvement, which results in the non-significant $\beta-$ coefficient and $\lambda-$ coefficient. All provinces in the Yangtze River Delta economic zone are rapidly promoting energy efficiency, so this zone does not reflect a significant catching-up effect. The Great Southwest economic zone has rich energy and mineral resources, which cause the economy to become too dependent on energy consumption. Therefore, the energy efficiency of the Great Southwest economic zone shows no improvement in the long term, which significantly affects the regional imbalance in energy efficiency.

5.2. Convergence Analysis of Energy Efficiency during Different Time Intervals

Based on the previous analysis, we found that Chinese regional energy efficiency has evolved differently during different Five-Year planning periods. According to the different stages of energy structure improvement and technology upgrading, we divided the entire sample period into two time intervals—1991–2005 and 2006–2015—and then we studied the energy efficiency convergence characteristics during each time interval. We present the estimation results of the convergence models during the different time intervals for the full sample and the regional samples in Tables 11–13.

From the estimated convergence rates shown in Table 11, we found that during the period 2006–2015, $\beta-$convergence and $\sigma-$convergence rates had greater absolute values, and the

$\lambda-$convergence rate had a smaller value. Therefore, the convergence effects of Chinese regional energy efficiency based on $\beta-$convergence, $\sigma-$convergence, and $\lambda-$convergence are more significant than those that occurred during the period 1991–2005. All of these findings indicate that, in the recent ten years from 2006 to 2015, Chinese regional energy efficiency had a more obvious catching-up effect. Meanwhile, the adjustment speed of regional energy efficiency toward the efficient frontier has been accelerating. Through the comparison of energy planning policies between 1991–2005 and 2006–2015, we found that before the year 2005, energy planning policies focused on the contradiction between energy supply and energy demand. Some structural adjustment, technology innovation, and system reform were conducted, but the emphasis was completely different from current energy planning policies. For example, in the energy planning policies that were released in 2005, structural adjustment focused on enterprise scale integration, technology innovation focused on the extraction equipment level of coal, oil, and gas, and system reform focused on whether the market mechanism of energy prices was optimal. The energy planning policies that were in place after 2005 put greater emphasis on clean energy consumption, energy processing and transformation technology, and environmental protection. Therefore, the actual evolutionary trend of regional energy efficiency is consistent with energy development planning policies, which shows that national energy policies do promote regional energy efficiency globally across China.

From the estimation results listed in Table 12, we found that all convergence characteristics of energy efficiency in the three areas during the period 2006–2015 are more evident than during the period 1991–2005. During the period 1991–2005, the western area has no catching-up effect, and the energy efficiency of the western and central areas has a very low adjustment speed toward the efficient frontier. However, during the period 2006–2015, each area demonstrates an obvious catching-up effect, but the western area still has a very low adjustment speed toward the efficient frontier. All of these findings indicate that the eastern area has a greater catching-up effect and a faster adjustment speed toward the efficient frontier during the period 2006–2015, while the central area reduced the energy efficiency bias across the entire sample period from 1991 to 2015. In addition, the central area has a λ adjustment speed that is similar to that of the eastern area during the period 2006–2015, which indicates that the central area has actively adjusted its industrial structure to improve energy efficiency in the past ten years. However, the energy efficiency of the western area showed a slow improvement, which expanded the differences in regional energy efficiency. Therefore, the energy efficiency of different provinces is not highly fluid between different levels in the long run [29], and the current regional structural characteristics of energy efficiency in the western area are not conducive to regional equilibrium and sustainable development.

From the estimation results shown in Table 13, we found that many convergence characteristics of energy efficiency in the seven economic zones during the period 1991–2005 were not significant, while most of them became significant during the period 2006–2015, especially for the $\beta-$convergence and $\lambda-$convergence. The Pearl River Delta had a stronger catching-up effect during the period 1991–2005, while the Yangtze River Delta had a stronger catching-up effect during the period 2006–2015. Other economic zones had a weak or insignificant catching-up effect. During the period 2006–2015, the Yangtze River Delta had significant $\beta-$convergence and $\lambda-$convergence rates, which indicates that the energy efficiency of the Yangtze River Delta has grown rapidly. Moreover, most of the economic zones' energy efficiency converged toward the efficient frontier during the period 2006–2015. The Central Bohai and Central Provinces economic zones had persistent inefficiency during the period 1991–2005, but the Central Provinces economic zone demonstrated a distinct improvement during the period 2006–2015. According to the convergence characteristics of the different economic zones, we found that on the whole, Chinese regional energy efficiency is improving, but the differences in the evolution characteristics of energy efficiency are still serious.

6. Conclusions and Policy Implications

In this paper, we have measured regional energy efficiency in China using a new weighted SBM method based on energy substitutability, which considers the relative importance of the different input indicators in the production process. By combining the translog production function with an econometric analysis technique, we were able to estimate the input weights. Empirically, we have comprehensively analyzed the evolution trends and convergence characteristics of Chinese energy efficiency from many aspects, including different areas, different economic zones, and different Five-Year plan periods. Further, we have made a comparative analysis according to different energy planning policies. All of these findings may provide useful guidance for regional coordinated development in the future.

From the empirical evidence, we observed that energy efficiencies across years and provinces in China are significantly different. The volatility of provincial energy efficiency has a rising trend over the period 1991–2015, and the improvement of energy efficiency is unbalanced across provinces. Chinese regional energy efficiency increases from west to east, given the advantages of the west in terms of location and industrial structure, and it is difficult to reduce these differences in the short term. The Yangtze River Delta, the Central Bohai area, and the Pearl River Delta economic zones have higher energy efficiency. Therefore, regional energy efficiency in China is characterized by a pattern of "high in the east and low in the west, and high in the south and low in the north". Although the energy efficiency of each area or economic zone has its own change trend during different five Five-Year planning periods, there are significant improvements during the Eleventh and Twelfth Five-Year plans. Further, the energy efficiency convergence results show that there are different convergence rates for different areas and economic zones over different time intervals, by which we discovered the imbalance of regional energy efficiency at a deeper level. Meanwhile, through a comparative analysis between energy planning policies and energy efficiency trends, we found that national energy policies do have a positive effect on the development of energy efficiency globally across China. However, the differences and fluctuations in regional energy efficiency remain serious, which is not conducive to the sustainable development of regional economic and energy policies in China.

Comparing our conclusions with the extant literature, we have found some similarities and differences in the sustainable evolution and convergence characteristics of energy efficiency. All of these findings are based on the energy efficiency measured by our proposed weighted SBM model considering energy substitutability. The key energy substitutability weights were computed from the estimators of the translog production function, which were decided by the ridge parameter. Although the empirical results of this paper are presented based on a given ridge parameter, the differences in energy substitutability weights were small between other ridge parameters, so it will not affect the core conclusions of this paper. In addition, any efficiency measured based on the DEA-SBM framework would have the problems that the efficient comparators will be weakened by the uncertainty due to finite sample bias. The long sample period in our paper can help mitigate this sample bias problem and ensure that the research results on energy efficiency are more robust.

To reduce regional differences and promote sustainable development, the Twelfth Five-Year plan indicates that China will promote the orderly transfer of industries and optimize industrial layouts among regions. Although a regional industrial structure has been optimized, the difference in energy efficiency has not decreased significantly. The approach to industry transfer places emphasis on the "resource utilization type", and the eastern area is shifting energy-intensive and labor-intensive traditional industries to other areas, which has increased the burden of energy consumption for central and western areas. Therefore, in accordance with current development planning and policies, we propose some important policy implications based on our research. First, an industry transfer policy should consider regional characteristics such as resources, environment, and techniques in order to guide the industry transfer correctly. During the process of industry transfer and upgrading, we should simultaneously consider low-end and high-end industries and optimize the industrial chain structure to balance the industrial advantages. Second, central and western areas mainly conduct inefficient energy industries such as coal, nonferrous metals, and chemicals; therefore, the differences in energy efficiency between the eastern, central, and western areas have not decreased. The government should provide flexible policies that promote effective industry transfer. Meanwhile, the central and western areas should concentrate the scale of their industrial activity to create a competitive advantage for high value-added energy products. Moreover, relying on the leading role of "One Belt and One Road" construction, the local governments of the central and western provinces should actively undertake the transfer of foreign investment and techniques from international and coastal areas. Third, the southeast coastal region should utilize technological advantages to foster new industries. Other economic zones should take advantage of geographical advantage to seek reasonable industrial layouts. Fourth, the lack of skills and talent has a critical influence on the differences in energy efficiency between the eastern and western areas, and financial support for talent introduction in the central and western areas is less than in the eastern area. Therefore, when implementing industry transfer from east to west, enterprises should establish a talent assistance and sharing mechanism to make up for the lack of talent, and the government needs to provide corresponding strong support and safeguarding measures.

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