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Convergence Analysis of Regional Energy Efficiency in China based on Large-dimensional Panel Data Model

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Abstract: With the advent of the era of big data, large-dimensional spatial panel data is gradually used to do empirical research in the macroeconomic field. This paper adopts a Data Envelopment Analysis (DEA) approach to calculate regional energy efficiency based on the perspective of total-factor energy efficiency using statistical data of 30 administrative regions in China. On basis of spatial effects, the paper assesses the convergence of regional energy efficiency in China using large-dimensional spatial panel data model. Our results indicate that (1) There is significant spatial autocorrelation and clear spatial effects in China's regional energy efficiency. Thus, spatial effects should not be ignored when assessing the convergence of regional energy efficiency in China; (2) During the period from 2000 to 2014 China's regional energy efficiency not only exhibits absolute β-convergence but also exhibits conditional β-convergence, the convergence rate is higher than the rate of absolute convergence after controlling for the initial conditions of the level of economic development, foreign direct investment and government influence; (3) The convergence rate of China's regional energy efficiency from 2004 to 2014 is higher than the convergence rate for the period of 2000 to 2004, which indicates that industry transfer has contributed to improvement in the convergence of regional energy efficiency in China

since 2004.

Keywords: energy efficiency; convergence; spatial effect; industry transfer; large-dimensional panel data model

1. Introduction

Steady economic growth requires a commensurate increase in energy inputs, while improved energy efficiency will offset the "growth effects" of energy input and attenuate the imbalance between energy supply and demand in the process of rapid economic growth(Song et al., 2013). When analyzing energy efficiency in China, two well-known facts should be considered. The first is that due to the long-term restrictions imposed by the country's extensive mode of economic growth and level of economic development, China's energy efficiency remains at a low level relative to those of developed countries(Zhao et al., 2015). The second is that the spatial distribution of energy efficiency in China reflects the unbalanced growth of China's regional economies; specifically, energy efficiency decreases in the level of economic development in the eastern, central and western areas. Low levels of energy efficiency inevitably lead to high levels of both energy consumption and pollution and reduce the imbalances in the spatial distribution of energy efficiency(Guo et al., 2015). This leads to the convergence of regional energy efficiency from low levels to a high level, which has the potential to significantly improve overall energy efficiency in China.

In recent years, scholars in many countries have devoted substantial attention to the problem of calculating and assessing the convergence of regional energy efficiency, and the primary contributions in the field include: Noailly (2011) analyzed improvements in energy efficiency from the perspective of the impact of environmental policy on technological innovation by analyzing seven European countries from 1999 to 2004. Jakobt et al. (2012) demonstrated that the convergence of energy efficiency is conducive to economic growth using panel data on 30 developing countries and 20 developed countries between 1971 and 2005. Baležentis et al. (2011) found that energy efficiency declines during economic downturns by measuring and calculating the energy efficiency of LTU between 1995 and 2009, using the LMDI method. Herrerias(2012) applied the weighted distribution dynamics approach to determine the energy efficiency levels of 83 countries, and indicated that the degree of the convergence of energy efficiency in developing countries is high. Meng(2013) conducted an empirical study on the conditional convergence of energy efficiency using the data of 25 European countries between 1960 and 2010. Stern (2012) found that the higher a country's energy efficiency level, the greater its total factor productivity (TFP), moreover, the convergence of regional energy efficiency was observed in an analysis of energy efficiency in 85 countries over 37 years using the stochastic frontier production function. Zou et al. (2015) applied the hybrid meta-frontier data envelopment analysis model to estimate the regional energy efficiency in China during 2003-2012, and based on it, point out that central and northeastern areas have a convergence tendency, whereas the energy efficiencies of the eastern and western areas in China show the characteristics of slight divergence, moreover, the convergence tendency of energy efficiency for the whole country has not yet been formed. Qi (2007) performed an empirical analysis of China using panel data, which divided China into eastern and

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western areas, the results reveal that as levels of GDP per capita converge, differences in energy consumption intensity between the western and eastern areas decline, but the rate of convergence is lower than that observed for GDP per capita. Shi (2006) calculated the energy-saving capacities of different provinces only considered the coefficient of variation for energy efficiency for China as a whole and failed to assess the convergence of regional energy efficiency. Li and Huo (2010) employed an input-oriented DEA model to measure and analyze the convergence of three regions' energy efficiency in China from 1995 to 2006, they found that overall energy efficiency in China and that in the eastern and central areas exhibited steady convergence, while the west of the country exhibits weak divergence .Liu (2011) calculates the total factor energy efficiency and tests regional energy efficiency convergence, the study shows that the total factor energy efficiency exists convergence tendency in the nationwide and the less advanced region pursues the effect to be obvious. Xu and Guan (2011) empirically studied the convergence of regional energy efficiency, and found that during the sample period, regional energy efficiency in China display not only absolute convergence but also significant conditional convergence. Wang and Fan (2012) found that total factor energy efficiency has a significant convergence at the 1% level in three regions based on the absolute β convergence test, the convergence rate of western region is higher than the central and eastern areas and the western region exhibits a catch-up effect and convergence trend. Wang et al. (2012) investigated the convergence of regional energy efficiency of overall country and three major areas, empirical conclusions point out that there are not convergences of regional energy efficiency among overall China and its three major areas, and the risk of the widen gap of energy efficiency among China's provinces still exist. Chen et al. (2013) used the spatial error conditional β-convergence model to estimate the effects of technological diffusion on the convergence of society-wide energy efficiency, the results shows that the absolute β-convergence of society-wide energy efficiency can be separated into three phases from convergence to divergence, the positive effect of spatial factors on β-convergence of society-wide energy efficiency is gathering strength. Zhao et al. (2015) used the panel data to analyze the convergence of energy efficiency, and found that energy efficiency of all provinces are converging absolutely and relatively, which means energy efficiency gaps between provinces are gradually narrowing. Guo et al. (2015) evaluated the total factor energy efficiency of 28 provinces in China from 1996-2010 by using the SBM model, then analyzed the spatial convergence of provincial total factor energy efficiency, results shows that the gap of provincial total factor energy efficiency is gradually reduced with the absolute convergence rate being 1.49%. Apergis and Christou(2015) explored the convergence of energy productivity across 31 countries from 1972 to 2012 by using the convergence club algorithm developed by Phillips and Sul (2007), and the empirical results lead to the rejection of full convergence and to the presence of a certain number of clubs.

The references above indicate that the existing literature suffers from two limitations. First, the literature only considers the convergence of energy efficiency in China from a temporal perspective, assuming independence among regions and the absence of any interaction. However, an actual economy, a nation or a region, is not isolated. Instead, technological development has rendered

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communication among them increasingly convenient, resulting in energy efficiency spillovers and Diffusion Effects among regions. As previous studies neglect spatial effects, they are unlikely to precisely identify the formation mechanism of convergence of regional energy efficiency. At the same time, with the advent of the big data era and the improvement of statistical system, large-dimensional spatial panel data is gradually used to do empirical research in the macroeconomic field. Compared to time series data and cross section data, the advantage of spatial panel data lie in integrating the merits of cross section, spatial adjacent and time series. In this case, large-dimensional panel data model has become a focus in modern econometrics research, which make it possible to study the convergence problems of regional energy efficiency from temporal and spatial perspectives. Second, existing studies analyzing convergence in energy efficiency in China has yet to account for industry transfer factors. However, given the shifts in China's industrial distribution that occurred in above 2003, in which traditional manufacturing transfered from China's eastern areas to central and western area(Xu 2013; Hu 2013), this transfer is bound to affect China's regional energy efficiency. Based on this, we will comprehensively consider the impact of spatial effects and industry transfer and study the issue of regional energy efficiency convergence in China to develop possible means of designing appropriate energy policies and provide a basis for decisions regarding the regional energy efficiency convergence.

This paper contributes to the literature in two ways. First, the methods adopted in this paper consider the interactions among regions, as analyzed using large-dimension spatial panel model, and the regional spatial effects will be included in the analysis of energy efficiency convergence in contrast to prior studies that simply considered the method of Time Series analysis. Second, we considers 2004 as a transition point, when industry in China's eastern coastal areas transfered to the central and western areas, and performs empirical tests on regional energy efficiency convergence before and after 2004, revealing the mechanisms driving improvements in China's regional energy efficiency convergence during the process of industrial relocation.

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2. Methods

2.1 Method for measuring energy efficiency

Currently, the most common methods for calculating energy efficiency are Single Factor energy efficiency and Total Factor energy efficiency. As the Single Factor method measures the proportional relationship between energy input and output, without accounting for the influence of the production processes of other input factors, this measure of energy efficiency has numerous limitations(Song et al., 2014). To address these limitations, Jin-Li Hu (2006)developed the Total Factor energy efficiency measurement based on the Total Factor Productivity (TFP) framework. The present paper applies the DEA method to measure energy efficiency by adopting the concept of Total Factor Productivity and treating energy as an input in the production function framework. The production function can be described as follows $Y = Af(K, L, E)$, where Y represents output variables and K, L, E represent capital, labor and energy, respectively. Using the DEA approach solves the problems associated with the use of multiple inputs and outputs.

DEA（data envelopment analysis）is a mathematical linear programming process used to evaluate the efficiency of a decision-making unit (DMU). Its purpose is to determine a non-parametric Envelope Frontier line. Efficient points are located on the production frontier, and inefficient points are located below the Frontier. Assuming that the number of DMUs is N, each unit uses K factors as inputs to produce M types of outputs; thus, the efficiency of the i-th DMU is determined by solving the following linear programming problems:

$$\begin{aligned} & Min\ \theta \\ & s.t. \quad -y_i + Y\lambda \geq 0 \\ & \theta x_i - X\lambda \geq 0 \\ & \lambda \geq 0 \end{aligned} \qquad (1)$$

where θ is a scalar with $0 \leq \theta \leq 1$, λ is a N×1 vector of constants that form a convex combination of observed inputs and outputs. The value of θ represents the technically efficient score for the ith DMU. The ith DMU is the most efficient point on the frontier and is technically efficient if θ=1, if θ<1 indicates that the ith DMU is technically inefficient.

The amount of total adjustments in energy input is regarded as the inefficient portion of actual energy consumption in a region. The more the amount of total adjustments, the less efficient the energy consumed in the region. Thus, if there does not exist an amount of total adjustments of energy input (equal to zero), then the region is utilizing energy at the 'target energy input' level, which is the optimal efficiency of energy consumption when its output is maximized. Therefore, energy efficiency in a region is defined in Eq.(2) as below, which is named total-factor energy efficiency (TFEE) for DMU i at time t can be measured as (Hu and Wang,2006):

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$$TFEE_{(i,t)} = \frac{TEI(i,t)}{AEI(i,t)} = \frac{AEI(i,t) - TA(i,t)}{AEI(i,t)} \qquad (2)$$

Where the target energy input (TEI) in this study is therefore actual energy input (AEI) minus the total adjustments (TA),which represents a practical minimum level of energy input to be taken as a target to perform at the optimal energy consumption efficiency.

2.2 Method for spatial auto-correlation analysis

The spatial effects of regional energy efficiency are primarily reflected in two measures: spatial correlation and spatial heterogeneity. Spatial correlation is evinced by spillover effects and Diffusion Effects within a given neighborhood. Spatial heterogeneity primarily indicates that due to a lack of geographical homogeneity across regions, energy efficiency exhibits distinct spatial differences(Sun et al., 2016). The spatial effect can be determined through an index called $Moran'I$, and the $Moran'I$ index is calculated as follows

$$Moran'I = \frac{n}{\sum_i \sum_j w_{ij}} \times \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad (3)$$

where w_{ij} is the element in the weights matrix corresponding to observation pair i-j, x_i and x_j are observations for regions i and j, n is the number of cross section. Moran'I index value is range of [-1,1].

Moran'I index greater than zero means that there have positive spatial connection among the observations, and the adjacent space regions have similar properties. Moran'I index smaller than zero means that there have negative spatial connection among the observation, and the adjacent space regions have different properties. When Moran'I index is equal to zero, there is no spatial connection among the observations.

The observed value is only independent and randomly distributed in space when the expected value approaches $-\frac{1}{n-1}$ (Pan et al., 2006). After calculating $Moran'I$, a Z test is generally used to assess statistical significance.

$$Z = \frac{[I - E(I)]}{\sqrt{Var(I)}} \quad (4)$$

2.3 Method for calculating convergence

2.3.1 The traditional convergence model

Convergence model is a widespread method for calculating the income distribution among countries or regions. The most important concept of convergence models is β-convergence. β-convergence is primarily based on the Convergence Hypothesis of the neoclassical economic growth model and means that regions with relatively lower initial levels of economic development exhibit higher growth rates than regions with higher levels and the growth rate and the initial level of economic development are negatively correlated(Hao et al., 2015). Generally, β-convergence can be divided into absolute β-convergence and conditional β-convergence; absolute β-convergence is determined as follows:

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$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta\ln(y_{i,t}) + \varepsilon_t \quad (5)$$

where $y_{i,t}$ is the level of energy efficiency of the ith region in year t, T is the length of the observation period, α and β are sample regression coefficients. If the value β is significantly negative, then there is a significant negative correlation between the growth of energy efficiency and the energy efficiency of base period, low-efficiency area has the trend of catching up with high-efficiency area, the absolute β convergence exists. ε is an unobserved disturbance term.

The equation for β-convergence includes control variables that are not considered under absolute β-convergence, and conditional β-convergence is calculated as follows:

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right) = \alpha + \beta_1\ln(y_{i,t}) + \beta_2 X_{i,t} + \varepsilon_t \quad (6)$$

Where $X_{i,t}$ is some conditional variable.

2.3.2 The convergence model with spatial effects

The above β-convergence analysis is performed using traditional measurement methods, while we will use large-dimension spatial panel error model and spatial panel lag model to study the convergence of regional energy efficiency.

1) Absolute β-convergence with spatial effects

The spatial panel error model of absolute β-convergence is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta\ln(y_{i,t}) + (I-\lambda W)^{-1}u_t \quad (7)$$

where λ is the spatial error coefficient, W is a spatial weight coefficient, μ_t is random error term.

The spatial panel lag model of absolute β-convergence is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta\ln(y_t) + \rho W\ln(\frac{y_{i,t+T}}{y_{i,t}}) + \varepsilon_t \quad (8)$$

where ρ is the spatial error coefficient, W is a spatial weight coefficient, ε_t is random error term.

2) Conditional β-convergence with spatial effects

The spatial panel error model of conditional β-convergence is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta_1\ln(y_{i,t}) + \beta_2 X_{i,t} + (I-\lambda W)^{-1}u_t \quad (9)$$

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The spatial panel lag model of conditional β-convergence is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta_1\ln(y_{i,t}) + \beta_2 X_{i,t} + \rho W\ln(\frac{y_{i,t+T}}{y_{i,t}}) + \varepsilon_t \quad (10)$$

2.3.3 The convergence model with industry transfer

Inorder to study the impacts of industrial transfer on the convergence regional energy efficiency, we will add dummy variable of $time_i$ to the model of Eq.(7) and Eq.(9), where $time_i$ equals 0 if the sample period is before 2004, and 1 otherwise. If the value of η is significantly negative, it indicates that the convergence rate in the period of 2004-2014 is higher than the rate in the period of 2000-2004. It also means that industry transfer has a positive impact on the convergence of energy efficiency. If the value of η is significantly postive, indicating that industry transfer will reduce the rate of energy efficiency convergence.

3) Absolute β-convergence with industry transfer

The spatial panel error model of absolute β-convergence with industry transfer is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta\ln(y_{i,t}) + \eta \bullet time_i + (I-\lambda W)^{-1}u_t \quad (11)$$

The spatial panel lag model of absolute β-convergence with industry transfer is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta \ \ln(y_t) + \eta \bullet time_i + \rho W \ln(\frac{y_{i,t+T}}{y_{i,t}}) + \varepsilon_t \tag{12}$$

4) Conditional β-convergence with industry transfer

The spatial panel error model of conditional β-convergence with industry transfer is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta_1 \ln(y_{i,t}) + \beta_2 X_{i,t} + \eta \bullet time_i + (I - \lambda W)^{-1} u_t \tag{13}$$

The spatial panel lag model of conditional β-convergence with industry transfer is

$$\frac{1}{T}\ln(\frac{y_{i,t+T}}{y_{i,t}}) = \alpha + \beta_1^{'} \ln(y_{i,t}) + \beta_2 X_{i,t} + \eta \bullet time_i + \rho W \ln(\frac{y_{i,t+T}}{y_{i,t}}) + \varepsilon_t \tag{14}$$

3. Empirical Analysis

3.1 Data and variables

Our aim is to conduct an energy efficiency analysis based on data for the variables of Capital Stock, Labor Force and Energy Consumption, which represent input factors from 30 provinces, municipalities and autonomous regions in China and considering each province's GDP as the output factor. For reasons of data consistency and availability, Tibet, Taiwan, Hong Kong and Macao are not included in the study.

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1) GDP output: operationalized using data on annual provincial GDP and the GDP deflator index taken from *China Statistical Yearbook* 2001-2015, measured in constant price GDP during the investigated period (using 2000 as the base year).

2) Capital Stock: the Perpetual Inventory Method is used to calculate the capital stock, the equation for which is $K_{it} = I_{it} + (1 - \delta_{it}) K_{it-1}$, where K_{it} and I_{it} are the Capital Stock and Investment in region i in the t-th year and δ_{it} is Depreciation Rate for Fixed Assets (Shan, 2004). The constant price of Capital Stock in 2000 values can be calculated after the conversion.

3) Labor Force: data are taken from the *China Statistical Yearbook* 2001-2015, and the employment level in the current year is described as Employment at the end of the current year. Due to missing data, provincial differences in labor quality are not included.

4) Energy: the annual energy consumption of each province captures energy input, which is converted into standard coal equivalents, and the data are collected from *China Energy Statistical Yearbook* 2001-2015. Because the data of Ningxia's energy consumption in 2000, 2001 and 2002 cannot be found in *China Energy Statistical Yearbook*, we complement the missing data from *Ningxia Statistical Yearbook* 2001, 2002 and 2003.

5) Regional division: following the traditional method, China is divided into the East, Central, and West regions. The East includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; Central includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the West includes Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, and Inner Mongolia.

3.2 Measuring regional energy efficiency

The energy efficiency of China's 30 provinces during 2000 to 2014 is calculated using MaxDEA software, Table 1 and Figure 1 presents the results.

Table 1 Regional and provincial energy efficiency levels in China during the period from 2000 to 2014

Region/province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	average
Beijing	0.87	0.92	0.92	0.94	0.93	0.97	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90	0.96
Tianjin	0.62	0.65	0.69	0.73	0.72	0.77	0.77	0.77	0.80	0.80	0.80	0.78	0.77	0.77	0.82	0.75
Hebei	0.38	0.37	0.36	0.36	0.36	0.39	0.39	0.39	0.40	0.40	0.40	0.40	0.41	0.41	0.45	0.39
Shanxi	0.27	0.24	0.23	0.24	0.26	0.24	0.24	0.24	0.25	0.25	0.26	0.26	0.26	0.25	0.24	0.25
Inner Mongolia	0.33	0.32	0.30	0.28	0.26	0.32	0.32	0.32	0.33	0.34	0.35	0.34	0.34	0.30	0.22	0.31
Liaoning	0.40	0.40	0.44	0.44	0.47	0.53	0.53	0.54	0.55	0.55	0.56	0.55	0.55	0.58	1.00	0.54
Jilin	0.47	0.47	0.45	0.44	0.46	0.54	0.55	0.56	0.57	0.58	0.57	0.55	0.57	0.61	0.63	0.53
Heilongjiang	0.47	0.49	0.50	0.54	0.51	0.58	0.58	0.59	0.59	0.60	0.61	0.61	0.60	0.90	0.70	0.59
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1
Jiangsu	0.83	0.85	0.88	0.87	0.82	0.82	0.83	0.84	0.84	0.85	0.85	0.84	0.84	0.85	1.00	0.85
Zhejiang	0.80	0.78	0.76	0.76	0.79	0.85	0.85	0.86	0.87	0.87	0.87	0.86	0.87	0.87	0.88	0.84
Anhui	0.50	0.51	0.53	0.56	0.59	0.65	0.66	0.66	0.67	0.67	0.69	0.69	0.68	0.67	0.75	0.63
Fujian	1.00	1.00	1.00	1.00	1.00	0.91	0.91	0.92	0.91	0.89	0.89	0.85	0.86	0.85	0.96	0.93
Jiangxi	0.68	0.68	0.67	0.64	0.67	0.72	0.73	0.73	0.75	0.75	0.75	0.74	0.75	0.75	0.75	0.72
Shandong	0.56	0.55	0.52	0.52	0.52	0.57	0.57	0.58	0.59	0.60	0.61	0.61	0.61	0.63	0.72	0.58
Henan	0.54	0.54	0.55	0.51	0.48	0.53	0.53	0.53	0.54	0.55	0.55	0.55	0.56	0.55	0.63	0.54
Hubei	0.48	0.50	0.51	0.49	0.46	0.51	0.51	0.52	0.53	0.54	0.55	0.55	0.54	0.53	0.78	0.53
Hunan	0.74	0.69	0.64	0.60	0.56	0.54	0.54	0.54	0.56	0.56	0.56	0.56	0.57	0.57	0.72	0.6
Guangdong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.995
Guangxi	0.66	0.64	0.68	0.65	0.59	0.64	0.63	0.64	0.63	0.63	0.62	0.59	0.58	0.57	0.63	0.63
Hainan	0.86	0.85	0.84	0.82	0.84	0.93	0.91	0.89	0.87	0.84	0.85	0.75	0.74	0.74	0.76	0.83
Chongqing	0.58	0.58	0.61	0.64	0.62	0.49	0.49	0.50	0.50	0.51	0.51	0.51	0.52	0.58	0.64	0.55
Sichuan	0.51	0.52	0.51	0.46	0.46	0.50	0.51	0.51	0.51	0.52	0.53	0.53	0.54	0.55	0.63	0.52
Guizhou	0.20	0.21	0.22	0.20	0.21	0.27	0.27	0.27	0.28	0.28	0.28	0.28	0.28	0.27	0.31	0.26
Yunnan	0.49	0.47	0.46	0.46	0.45	0.46	0.45	0.46	0.46	0.46	0.46	0.46	0.45	0.50	0.49	0.47
Shaanxi	0.58	0.54	0.52	0.51	0.49	0.51	0.51	0.52	0.53	0.53	0.53	0.53	0.52	0.51	0.50	0.52
Gansu	0.30	0.31	0.33	0.32	0.33	0.36	0.36	0.36	0.36	0.37	0.38	0.37	0.37	0.37	0.36	0.35
Qinghai	0.25	0.26	0.26	0.27	0.25	0.25	0.24	0.24	0.24	0.25	0.25	0.22	0.21	0.21	0.21	0.24
Ningxia	0.29	0.29	0.28	0.21	0.16	0.18	0.17	0.17	0.18	0.18	0.19	0.17	0.17	0.16	0.15	0.2
Xinjiang	0.37	0.38	0.39	0.38	0.36	0.37	0.36	0.36	0.35	0.34	0.33	0.30	0.26	0.23	0.23	0.33
East	0.76	0.76	0.77	0.77	0.77	0.79	0.80	0.80	0.80	0.80	0.80	0.79	0.79	0.79	0.86	0.79
Central	0.52	0.52	0.51	0.50	0.50	0.54	0.54	0.55	0.56	0.56	0.57	0.56	0.57	0.61	0.65	0.55
West	0.41	0.41	0.42	0.40	0.38	0.39	0.39	0.39	0.40	0.40	0.40	0.39	0.39	0.39	0.40	0.4

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Table 1 indicates that Shanghai is the province with the highest energy efficiency, and it is located on the production frontier during 2000 to 2014. Guangdong, Beijing, and Fujian are located on the production frontier for many years. Qinghai and Ningxia are the provinces with the lowest energy efficiency, which are both below 0.25. Regarding the regional distribution of energy efficiency in China, energy efficiency value of the eastern areas is the highest with an average value of 0.79 for the 15 years considered; the central area is followed by the eastern areas with an average value of 0.55 during this period. While the energy efficiency of the western area is the lowest with an average value of 0.4. Clearly, These findings suggest that the regional energy efficiency in China presents a decreasing pattern from the coastal to the inland areas.

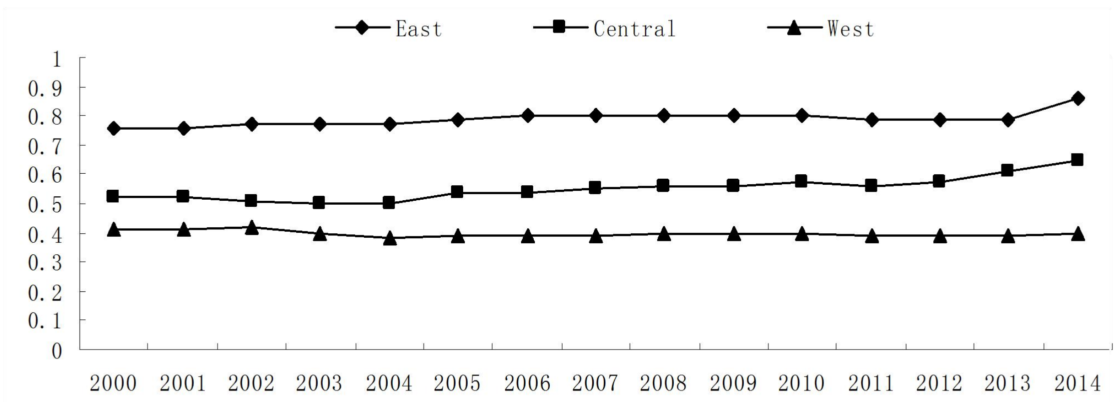

Figure 1 The changing trend of Regional energy efficiency in China during the period from 2000 to 2014

The reason for this distribution may be related to geographical location and industrial structure. On one hand, most provinces with higher energy efficiency are located in the eastern coastal areas, which are due to their advantageous geographical locations to get better support, such as capital, technology and information, than the inland areas. To a certain extent, the spatiotemporal distance between inland and coastal regions hinders the entry of capital, technology and information, which make the energy efficiency in inland areas remain at a lower level. On the other hand, most regions with higher energy efficiency have a higher level of industrial structure and better market development. Since reform and opening up, Guangdong, Shanghai, Fujian, Zhejiang, Jiangsu, and other southeastern coastal areas carry out "walking out" strategy. With the development of an export-oriented economy, these regions realize the adjustment and optimization of the industrial structure. They established a highly standardized market economic system, transformed the model of extensive economic growth depending purely on the input of resources into intensive ones, and developed an industrial structure mainly composed of the service industry and high-tech industry. The continuous adjustment and optimization of the industrial structure in the coastal areas can not only improve their own energy efficiency, but also the economic development and energy efficiency in the surrounding areas. The industrial structure of the central and western regions is low, which is mainly composed of traditional resource-based industry. The technical level and energy efficiency are relatively fall behind despite the noticeable development of electricity, coal, oil, and other characteristic industries. An upward trend on energy efficiency has been evident in the central and western provinces of China in recent years. This phenomenon suggests that the implementation of energy conservation and emissions reduction strategy in China has been substantially achieved(Song et al.,2015).

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3.3 Testing the spatial effects of regional energy efficiency

Using Geoda software, we calculate the value of $Moran'I$ index based on the rules of rook contiguity spatial weights, Table 2 presents the results.

Table 2 Moran'I test of energy efficiency in China during the period from 2000 to 2014

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Moran'I	0.481	0.481	0.479	0.478	0.497	0.500	0.503	0.504	0.516	0.516	0.512	0.517	0.525	0.467	0.480
Z	4.331	4.408	4.509	4.345	4.614	4.575	4.559	4.568	4.634	4.596	4.627	4.663	4.864	4.067	4.303
P	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001	0.002	0.001

Table 2 indicates that in each period, regional energy efficiency in China exhibits positive spatial correlation at the 1% significance level, and hence regional energy efficiency in China is influenced by its neighboring area. Some study also proved that there exists the significant spatial autocorrelation in China's regional energy efficiency(Yang and Liu,2014; Zhang and Feng,2015). Therefore, regional energy efficiency is not randomly distributed in space but is intrinsically linked to that of other regions and exhibits a tendency to cluster during the period investigated. The results indicate that the spatial effects should not be ignored when studying on the convergence of energy efficiency in China.

3.4 Testing the convergence of regional energy efficiency

Having analyzed the spatial effects influencing regional energy efficiency, we conduct empirical tests on absolute convergence and conditional convergence of regional energy efficiency in China using large-dimensional spatial panel data model and reveals convergence of energy efficiency in China.

3.4.1 Absolute β-convergence analysis

Using Matlab software, we test the absolute β-convergence of regional energy efficiency using Eq.(7), Eq. (8), Eq. (11) and Eq. (12). Table 3 presents the results.

Table 3 absolute β-convergence test results for China during the period from 2000 to 2014

model	not considering industry transfer		considering industry transfer	
	SEM(Eq.(7))	SLM(Eq.(8))	SEM(Eq.(11))	SLM(Eq.(12))
β	-0.175(-4.816)***	-0.157(-4.435)***	-0.153(-4.213)***	-0.146(-4.134)***
ρ/λ	0.295(5.032)***	0.262(4.432)***	0.248(4.107)***	0.222(3.667)***
η			-0.033(-3.133)***	-0.028(-3.269)***
R-squared	19.06%	14.13%	20.8%	17.58%
corr-squared	4.56%	3.92%	8.34%	8.07%
LOG(L)	582.566	580.934	587.529	586.542
sigma^2	0.0038	0.0039	0.0038	0.0038
LM-test	21.1674(0.000)	1.8526(0.173)	12.9613(0.000)	1.0928(0.296)
Robust LM-test	13.494(0.000)	1.7295(0.188)	7.9976(0.005)	0.9699(0.325)

Note: (1) The figures in parentheses below the parameter estimates are t-statistics; the figures in parentheses below the diagnostic test results, LM, Robust-LM, are p values. (2) *, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively. (3) The SEM and SLM models are estimated by Maximum Likelihood (ML).**

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The absolute β-convergence test results in Table 3 can be summarized as follows:

1) When not considering industry transfer, the value of R-squared(19.06%), LOG(L)(582.566), LM(21.1674) and Robust-LM(13.494) in SEM that are better than those of the corresponding SLM results, and both are significant at the 1% level, indicating that SEM is more appropriate than SLM to estimate absolute β-convergence. The value of β coefficient in SEM is -0.175, indicating that China's regional energy efficiency exhibits absolute β-convergence During the period from 2000 to 2014 and the convergence rate is 17.5%.

2) When considering industry transfer, the value of R-squared(20.8%), LOG(L)(587.529), LM(12.9613) and Robust-LM(7.9976) in SEM are better than those of the corresponding SLM results, and both are significant at the 1% level, indicating that SEM is more appropriate than SLM to estimate absolute β-convergence. The value of β coefficient in SEM is -0.153, indicating that China's regional energy efficiency exhibits absolute β-convergence During the period from 2000 to 2004 and the convergence rate is 15.3%. In addition, the value of η coefficient is -0.033 and is significant at the 1% level, indicating that compared with the period from 2000 to 2004, the convergence rate during the period from 2004 to 2014 is increased by 3.3%. It reflects that industry transfer is beneficial to absolute convergence of regional energy efficiency. The conclusion of Yu(2010)'s study show that industry transfer can effectively promote the energy efficiency of China's western area, and this, to a certain extent, supports our view here in this paper. The reasons for this are as follows: on the one hand,

against the background of China's energy strategy, the central and western area focus on improving energy consumption monitoring and energy assessment reviews, and pursue projects to strictly implement the relevant energy consumption standards during the process of industry transfer; on the other hand, the enterprises in the central and western area can absorb advanced technology, equipment and management experience during the process of industry transfer, which directly contributed to the improvement energy efficiency in the central and western area.

3.4.2 Conditional β-convergence analysis

The following section focuses on the analysis of the conditional β-convergence effect of regional energy efficiency, the purpose of which is to identify the factors affecting convergence of regional energy efficiency.

3.4.2.1 Selecting the convergence condition

Research on the impact of regional energy efficiency has attracted the attention of numerous scholars. Integrating the research in the existing literature, we consider the primary factors improving regional energy efficiency in China to include the level of economic development, foreign direct investment and government influence; thus the following assumptions were made.

Assumption 1: The level of economic development (rgdp) has a significant positive impact on energy efficiency. Energy is one of the key factors to underpin the development of China's economy, while the extensive economic growth pattern makes the problems of energy constraints more and more serious. To some extent, the level of energy efficiency might be effectively improved as China's economy is on its way. And we use per capita GDP to measure the level of economic development(Song, 2012).

Assumption 2: The foreign direct investment (fdi) reflects the extent to which a country is integrated into the global economic system. For a country or region, increasing the degree of fdi contributes to the acquisition of foreign capital, technical and management experience(Hübler and Keller,2010). All mentioned above have a significant impact on energy efficiency. We use the levels foreign direct investment as a share of GDP to measure the degree of foreign direct investment.

Assumption 3: Government's influence(gov) has a significant negative impact on energy efficiency. Generally, government regulation is always the main energy pricing mechanism in China, so that the actual energy price is unreasonable for the long run, which cannot truly reflect the supply-demand situation of energy market. Therefore, the influence of government is reducing the energy efficiency(Craig and Allen, 2014). We constructs a government influence index by Financial Expenditure in GDP.

3.4.2.2 Empirical calculation and results

Using Matlab software, we test the conditional β-convergence of regional energy efficiency using Eq.(9), Eq. (10), Eq. (13) and Eq. (14). Table 4 presents the results.

Table 4 conditional β-convergence test results for China during the period from 2000 to 2014

model	not considering industry transfer		considering industry transfer	
	SEM(Eq.(9))	SLM(Eq.(10))	SEM(Eq.(13))	SLM(Eq.(14))
β	-0.200(-4.954)***	-0.200(-5.507)***	-0.193(-4.850)***	-0.196(-5.021)***
ρ/λ	0.260(4.336)***	0.254(4.324)***	0.202(3.260)***	0.193(3.192)***
η			-0.040(-3.300)***	-0.033(-3.201)***
rgdp	0.024(4.667)***	0.023(4.914)***	0.022(4.359)***	0.021(4.533)***
fdi	-0.002(-0.094)	-0.003(-0.165)	0.020(1.007)	0.018(0.932)

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gov	-0.233(-2.452)**	-0.249(-2.929)***	-0.349(-3.853)***	-0.346(-3.856)***
R-squared	23.85%	19.76%	25.24%	22.97%
corr-squared	10.76%	10.99%	14.33%	14.38%
LOG(L)	594.001	593.968	599.295	599.291
sigma^2	0.0037	0.0037	0.0036	0.0036
LM-test	15.3000(0.000)	61.4258(0.232)	8.7131(0.003)	0.8291(0.363)
Robust LM-test	7.0170(0.008)	2.5395(0.111)	4.3517(0.037)	1.0484(0.306)

Note: (1) The figures in parentheses below the parameter estimates are t-statistics; the figures in parentheses below the diagnostic test results, LM, Robust-LM, are p values. (2) *, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% levels, respectively. (3) The SEM and SLM models are estimated by Maximum Likelihood (ML).**

The conditional β-convergence test results in Table 4 can be summarized as follows:

1) When not considering industry transfer, the value of R-squared(23.85%), LOG(L)(594.001), LM values(15.3) and Robust LM value(7.0170) in SEM during the period of 2000 to 2014 are better than those of SLM, and both are significant at the 1% level, indicating that SEM is more appropriate than SLM for estimating conditional β-convergence. The value of β coefficient in SEM is -0.2, indicating China's regional energy efficiency exhibits conditional β-convergence During the period from 2000 to 2014 and the convergence rate is 20%.

2) When considering industry transfer, the value of R-squared(25.24%), LOG(L)(599.295), LM(8.7131) and Robust-LM(4.3517) in SEM are better than those of the corresponding SLM results, and both are significant at the 1% level, indicating that SEM is more appropriate than SLM to estimate conditional β-convergence. The value of β coefficient in SEM is -0.193, indicating that China's regional energy efficiency exhibits conditional β-convergence During the period from 2000 to 2004 and the convergence rate is 19.3%. In addition, the value of η coefficient is -0.04 and is significant at the 1% level, indicating that compared with the period from 2000 to 2004, the convergence rate during the period from 2004 to 2014 is increased by 4%. indicating that industry transfer is also beneficial to conditional convergence of regional energy efficiency.

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3) During the periods 2000-2014, 2000-2004, and 2004-2014, after controlling the level of economic development, foreign direct investment and government's influence, the rate of conditional convergence increases more rapidly than that of absolute convergence, indicating that economic development, foreign direct investment and government influence are important factors affecting the convergence rate of regional energy efficiency; moreover, the level of economic development has positive effects, while the foreign direct investment and government influence have negative effects, which is consistent with the assumptions mentioned above.

4. Conclusions

By considering the factors of spatial effects and industry transfer, this paper conducts an empirical study on convergence of regional energy efficiency using large-dimensional spatial panel data model based on data from the period of 2000 to 2014 in China. The following is a summary of our conclusions:

(1) Using the $Moran' I$ test, we find that there exists the significant spatial autocorrelation in China's regional energy efficiency, which indicates that there are clear spillover effects and diffusion effects in China's energy efficiency. Therefore, prior studies adopting the OLS approach may have obtained biased estimates of convergence of China's regional energy efficiency, indicating that when assessing

convergence of China’s regional energy efficiency, spatial effects should not be ignored. Thus, to ensure that the energy efficiency of the central and western areas converge with those of the eastern areas, we must take full advantage of the spatial effects and strengthen the technological exchanges and cooperation among neighboring areas.

(2) The results of large-dimensional spatial panel data model indicate that during the periods of 2000 to 2014, China’s regional energy efficiency exhibits both the absolute β-convergence and conditional β-convergence. Moreover, the rate of conditional convergence obtained after controlling for the level of economic development, foreign direct investment and government influence was greater than the rate of absolute convergence. Therefore, to gradually reduce the regional gaps in China's energy efficiency, it is crucial to emphasize the factors of the level of economic development, foreign direct investment and government influence, screen foreign investment and take advantage of international markets and international resources to introduce more advanced technology, and meanwhile increase the level of government influence.

(3) During the period from 2004 to 2014, the rates of absolute convergence and conditional convergence are both greater than those from 2000 to 2004, indicating that industry transfer is beneficial to the promotion of convergence of regional energy efficiency. Therefore, in the future, we need to undertake industry transfer orderly and promote industrial upgrading in the central and western areas. Moreover, it is also necessary to strictly control projects with high levels of energy consumption in the process of industrial transfer and prohibit the introduction of industries that fail to satisfy China’s industrial policy and industrial technology policy.

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二〇一七年五月二十五日