Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 7, No. 3, 2023

Research on Regional Differences and Spatial Dynamic Evolution of Green Efficiency of China's Provincial Service Industry

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Abstract: In order to achieve the goal of "Peak Carbon Dioxide Emissions and Carbon Neutrality" as scheduled, China's service industry must achieve green development. In this paper, we use the super-efficiency SBM-DDF integration model to measure the green efficiency of the service industry in 30 provinces in China during 2011-2019. On the basis of the green efficiency level of the service industry, the Dagum Gini coefficient and the spatial Markov chain are used to analyze the source of the regional gap and the spatial dynamic evolution of the green efficiency of the service industry in China's four major regions. The results suggest that: (1) The overall green efficiency of China's service industry is increasing, and there is significant heterogeneity among regions. (2) The green efficiency of China's service industry has obvious characteristics of spatial differentiation. Regional differentiation is the main source of its spatial differentiation, and the contribution rate of over-density is the lowest. (3) The provinces with high service industry efficiency in China have a positive radiation effect on the green efficiency of the service industry in surrounding provinces, while the provinces with low-efficiency levels will have a certain inhibitory effect on the green efficiency of the service industry in surrounding provinces.

Keywords: Green efficiency of the service industry, Dagum Gini coefficient, Spatial Markov chain, SBM-DDF integration model.

1. Introduction

Since the reform and opening up, China's service industry has achieved remarkable results in employment and development scale, etc. In terms of employment, at the end of 2019, the total employment in the service industry was 367.21 million, accounting for 47.4% of employment in all sectors; in terms of the scale of output value, China achieved 53.43 trillion yuan in the tertiary industry in 2019, an increase of 6.9%. The proportion of the value of the primary industry to GDP is 7.1%, 39.0% in the secondary industry, and 53.9% in the tertiary industry; in terms of the service sector, the scale of China's digital economy has reached 31 trillion yuan in 2019, accounting for about one-third of GDP. since 2015, "conversion of old and new kinetic energy " appears frequently and " needs to be promoted urgently " in speeches and documents of leaders of the central and local governments. Since the proposal of " conversion of old and new kinetic energy ", the connotation of "new dynamics" is very broad, and the improvement of consumption capacity and the rapid development of tertiary industries or new industrial forms can become the "new dynamics" of economic development. "Consumption and services will gradually replace investment and exports as the main source of economic growth. However, the high environmental pollution and resource inefficiency brought about by the development of service industries have also become inescapable real problems (Alcántara and Padilla, 2009; Pang and Deng, 2014; Wang et al. 2015), while the severity of environmental pollution and resource waste problems vary significantly from region to region (Wang and Xu, 2020; Meng et al. 2021). According to the Green National Economic Accounting Study by the Environmental Planning Institute of the Ministry of Environmental Protection, it is reported that the cost of ecological degradation in China amounted to 1538.95 billion yuan in 2010, and the proportion of this cost to GDP was 3.5%; according to the Environmental Performance Index (EPI) report jointly published by the Center for Environmental Law and Policy (Yale University) and the International Center for Earth Science Information Network (Columbia University), the China's EPI score for 2014 was only 43 points, while the ranking continues to trend downward. According to the United Nations Environment Programme report (2020), China's greenhouse gas emissions reached 14093 million tons of carbon dioxide equivalent in 2019, accounting for more than 27% of total global emissions, far surpassing the United States, which ranked second.

The "14th Five-Year Plan" proposes to focus on industrial transformation and upgrading and the need for consumer upgrading, expand the effective supply of services, improve service efficiency and service quality, and build a new system of high-quality and efficient, structural optimization, competitive service industry. Guided by the high-quality development of the service manufacturing industry, promote the productive service industry to specialization and high-end extension of the value chain. We should make efforts to promote the structural reform on the supply side, adhere to the innovation drive, support the transformation and use of energy-saving and environmental protection equipment by service enterprises, cultivate green service enterprises, and promote the transformation and upgrading of green development in the service industry. The National Development and Reform Commission's guidance on the high-quality development of the service industry in the new era once again affirms the emphasis on deepening the structural reform of the supply side of the service industry, vigorously cultivating new industries, new industries and new models in the service industry, focusing on improving service efficiency and service quality, and solidly promoting the high-quality development of the service industry. As China's economy enters the "new normal" of development, the growth rate of economic development is slowing down, and the focus on the quality of development is more in line with the actual situation in China. In the process of economic development into the "new normal", the change of economic development momentum is an important part of high-quality development, which may bring downward pressure to the growth rate of China's economy, but will also promote the development of China's economy in the direction of green and healthy. In the "old and new dynamic energy conversion" of economic development, new dynamic energy must be highlighted, and in the supply side of new dynamic energy, the green and rapid development of the service industry is crucial. Therefore, governments at all levels are fully supporting the development of the service industry, and the upgrading of the service industry has become the top priority of economic development. Under such a background, it is required to improve the green efficiency of service industry while developing the service industry, and it is of great theoretical and practical significance to promote the regional coordinated development of the service industry to realize the transformation of new and old dynamic energy and promote the high-quality coordinated economic growth.

In China, some scholars have conducted research on green efficiency in China's service industry, but most of them measure green efficiency by means of total factor productivity (TFP), mainly by parametric methods - Stochastic Frontier Analysis (SFA) and non-parametric methods - Data Envelopment Analysis (DEA). The parametric methods mainly include the C-D production function method, the algebraic exponential method, and the transcendental logarithmic production function method. All three methods require specifying the specific form of the production function and accurately grasping the relevant price information of the input and output variables. In addition, the assumptions of the parametric method are relatively strict, requiring the production process to satisfy the assumption of constant returns to scale and to achieve full efficiency of production on the technological frontier. Due to the simplicity of the model of this method, many scholars at home and abroad have applied the parametric method to total factor productivity measurement in the early stage of research. However, accounting for green TFP requires the inclusion of pollutant emissions and energy consumption in the productivity measurement system, and the price of pollutants is difficult to obtain, so the assumptions of the parametric method are difficult to be met. The nonparametric method does not require setting specific production functions and can simulate the production process of multiple inputs and multiple outputs simultaneously, and this method, which does not require constructing specific production functions and can decompose productivity, has received much attention from many scholars at home and abroad and has achieved remarkable results in the application (Kumar, 2006; Yu et al. 2008; Han and Ma, 2019; Liu, 2019), but it is mainly applied at the medium and macro levels, and the application at the individual micro level is still relatively rare. Although the traditional total factor production measurement takes into account the "good" output produced in the production process, it ignores the hard constraints of resources and environment for current and future sustainable economic development, and the direct measurement of productivity without considering environmental factors will bring biased results (Nanere et al., 2007; Wang et al., 2010).), and also lead to misleading policy implications of TFP (Hailu and Veeman, 2000). And with the introduction of Chung et al.'s (1997) ML index based on the directional distance function, scholars began to introduce environmental pollution indicators into the system of measuring economic growth and reconstructed the green productivity measurement and evaluation index system under resource and environmental constraints (Hoang and Coelli, 2011; Li et al. 2017; Li and Xu, 2018; Du et al. 2019).

Different researchers have different insights into exploring the treatment of undesired outputs of environmental pollution and the choice of efficiency measurement models. There are three main approaches in the existing literature on the measurement of environmental pollution. The first one takes environmental pollution as an input factor directly into the production function (Chen et al., 2009), but this method is not in line with the input-output logic. The second one introduces pollution output into the production function with corresponding data transformation (Seiford and Zhu, 2005), but this transformation method is not in line with the logic and the measurement results lack reliability and rationality. The third one includes environmental pollution as "undesired output" in the total factor productivity measurement system, which has been more widely used in academia because it is more consistent with the real production process (Chen and Golley, 2014; Li et al., 2017). In terms of the selection of efficiency measurement models, traditional DEA models are based on radial and angular, while radial and angular DEA models have many assumptions in measuring TFP, thus making it difficult to ensure the accuracy of total factor productivity measurement results. To solve this, Tone (2001) proposed a non-radial, non-oriented SBM model by adding slack variables to the objective function, proposing a non-radial, non-oriented SBM model by adding slack variables to the objective function, but this model did not consider non-desired outputs, which are generated by service production activities, such as carbon dioxide, and therefore the model is not applicable to this study. In his later studies, Tone proposed the SBM model considering undesired outputs in a subsequent study, which compensated for the shortcomings of the previous model. However, the models all have difficulty in further differentiating the effective decision units, which leads to inaccurate evaluation results. the One Sup SBM model proposed by Hieu T T. et al (2018) can solve the problem better, but the model has two shortcomings, one is that it only considers constant returns to scale (CRS), and the other is that it does not consider non-desired outputs.

Some scholars have found regional heterogeneity and spatial convergence heterogeneity in the green efficiency of China's service industry. In terms of regional heterogeneity, some scholars found that service industry agglomeration increased the green productivity of the service industry in local and neighboring regions, while the positive effect of service industry agglomeration on service industry green productivity was mainly concentrated in eastern, western, and central regions (Wang Xu et al., 2020, Wang and He, 2021), while the spatial spillover effect in western regions and regions lagging behind in service industry was not obvious.

In addition, some scholars examined the spatial convergence of green efficiency in China's service industry and found that the convergence characteristics of green TFP in the service industry showed significant regional heterogeneity (Wang, Xu, and Xu, 2020; Meng, et al., 2021). Other scholars used the Dagum Gini coefficient to explore the degree of its spatial heterogeneity, as well as the use of geographic probes to investigate the drivers of its spatial heterogeneity, and found that the overall trend of green TFP in China's service industry is growing, but there are significant heterogeneity characteristics among regions, and the spatial differences of green TFP growth in China's service industry are widening, and the main cause of the spatial non-equilibrium problem The main reason for the spatial non-equilibrium problem is inter-regional differences (Teng et al., 2020; Chen and Wang, 2020).

In view of this, this paper will expand the study of regional differences and spatial evolution of green efficiency in China's service industry under resource and environmental constraints as follows: first, by improving the One Sup SBM model, an integrated model combining the one-stage SBM-DDF and the super-efficient SBM-DDF is obtained, which can not only solve the two problems of the One Sup SBM model but also obtain the efficiency of inefficient DMUs by solving the one-stage model to directly obtain the efficiency fraction of inefficient DMUs and the super-efficient fraction of effective DMUs. Second, the 30 provinces in China are divided into four regions (see Figure 1): the eastern region, the northeastern region, the central region, and the western region. Thus, it is important to explore the regional disparity of green efficiency of service industries among regions and its spatial dynamic evolution, which is of theoretical significance to narrow the regional efficiency gap and find ways to improve the overall green efficiency level of service industries. Finally, in order to comprehensively study the regional differences and trends of green efficiency in China's service industry, this paper selects the Dagum Gini coefficient and spatial Markov chain to analyze the sources of regional disparity and spatial dynamic evolution of green efficiency in sthe ervice industry in four major regions of China. Finally, on the basis of the above analysis, conclusions are drawn and corresponding policy recommendations are given.

Figure 1. Division of China's four regions

2. Empirical Model Construction and Data Source

2.1. Directional SBM-DDF integration model

According to the definition of Färe (2007), we assume that therare j evaluated DMUs, and each DMU uses N kinds of input factors $x_{nj}(n = 1,2, \ldots, N)$ to produce M kinds of expected outputs $y_{nj}(m = 1,2, \ldots, M)$ and i kinds of undesired output $b_{ij}(n = 1,2, \ldots, I)$. The environmental technology set of the DEA is defined as:

$$P(x) = \{(x, y, b): x \ can\ produce\ (y, b)\} \tag{1}$$

The output of environmental technology set P(x) with a given input must be limited, with closed, bounded, and convex characteristics. This environmental technology set P(x) satisfies the following conditions:

The first condition is that the output is expected to be strongly disposable. If $(y, b) \in P(x)$ and $y' \leq y$ then $(y', b) \in P(x)$. It means that under the given conditions of input and undesired output, expected output can change freely within a certain rangeThe differentnt expected output reflects the level of technical efficiency of each decision-making unit under environmental regulation.

The second condition is that the undesired output is weakly disposable. If $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$, then $(x, \theta y , \theta b) \in P(x)$. This means that the expected output and the undesired output will increase or decrease in the same proportion. The reduction of undesired output will inevitably lead to the reduction of expected output, which reflects the cost of pollution control.

The final condition is the null joint of expected output and undesired output. If$(y, b) \in P(x)$, and, $b = 0$ then $y = 0$. It emphasizes that in production activities, the expected output will inevitably be accompanied by pollution emissions. Only when the expected output is zero pollution emissions.

The concept of environmental technology set is mainly used in the study of cross-sectional data, that is, individual data for each year for calculation. However, during the sample period, comparing the data of each year separately, the results lack credibility and may deviate from the actual production situation. In order to overcome this shortcoming, the concept of Global Benchmark Technology was introduced into our research, which was defined by Oh (2010) as:

$$P^t(x^t) = \{(x^t, y^t, b^t): x^t\ can\ produce(y^t, b^t)\} , t = 1,2, \ldots, T \tag{2}$$

The global reference set means that the data of any period is included, which means that all input and output panel data are used to establish a common effective frontier $P^G = P^1 \cup P^2 \cup \ldots \cup P^3$. This means that all DMUs in the sample period is based on the same effective frontier when calculating energy efficiency, which is more comparable.

Combined with Hieu TT et al. (2018), we obtained an integrated model combining SBM-DDF and super-efficiency SBM-DDF. This model can directly obtain the efficiency scores of invalid DMUs and the super-efficiency scores of effective DMUs by solving the one-stage model.

The proposed model is described as follows:

$$min\theta_o = \alpha\rho_o + (1 - \alpha)\rho_o$$

$$s.t.: \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2(M+K)}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{n=1}^{N}\frac{z_k^b}{g_k^b}\right) \leq \alpha\overline{M} , \alpha\epsilon\{0; 1\}$$

$$x_{no}^t = \sum_{j=1}^{J} x_{nj}^t \lambda_{1j}^t + s_n^x , n = 1, \ldots, N$$

$$y_{mo}^t = \sum_{j=1}^{J} x_{mj}^t \lambda_{1j}^t - s_m^x , m = 1, \dots, M$$

$$b_{ko}^t = \sum_{j=1}^{J} x_{kj}^t \lambda_{1j}^t - s_k^x , k = 1, \dots, K$$

$$\sum_{j=1}^{J} \lambda_{1j}^t = 1, j = 1, \dots, J$$

$$\lambda_{1j}^t \ge 0,\ s_n^t \ge 0,\ s_m^y \ge 0, s_k^b \ge 0 \qquad (3)$$

$$x_{no}^t \ge \sum_{j=1, j\ne 0}^{J} x_{nj}^t \lambda_{2j}^t - z_n^x, n = 1, \dots, N$$

$$y_{mo}^t \ge \sum_{j=1, j\ne 0}^{J} y_{mj}^t \lambda_{2j}^t + z_m^{yx}, m = 1, \dots, M$$

$$b_{ko}^t \ge \sum_{j=1, j\ne 0}^{J} b_{kj}^t \lambda_{2j}^t - z_k^b, k = 1, \dots, K$$

$$\sum_{j=1, j\ne 0}^{J} \lambda_{2j}^t = 1, j = 1, \dots, J, j \ne 0$$

$$\lambda_{2j}^t \ge 0,\ z_n^t \ge 0,\ z_m^y \ge 0, z_k^b \ge 0$$

Where $\bar{M}$ is a large positive number; λ_{1j} and λ_{2j} are the non-negative vectors of the SBM-DDF model and the super-efficiency SBM-DDF model, respectively. The objective function is used to measure the super efficiency score of the effective DMU:

$$\rho_0 = 1 + \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} + \frac{1}{2(M+K)}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{n=1}^{N}\frac{z_k^b}{g_k^b}\right)$$

and the efficiency score of the ineffective DMU

$$\sigma_0 = 1 - \frac{1}{2N}\sum_{n=1}^{N}\frac{z_n^x}{g_n^x} - \frac{1}{2(M+K)}\left(\sum_{m=1}^{M}\frac{z_m^y}{g_m^y} + \sum_{n=1}^{N}\frac{z_k^b}{g_k^b}\right)$$

In the objective function, we use a binary variable $\alpha \in \{0; 1\}$ to convert the efficiency measurement of the SBM-DDF model and the super-efficiency SBM-DDF model. If $\alpha = 1$, the super-efficiency SBM-DDF model is selected as the calculated super-efficiency score. If $\alpha = 0$, the SBM-DDF model is selected as the calculated efficiency score.

2.2. Dagum Gini coefficient

In this paper, the Dagum Gini coefficient and its decomposition method are used to describe the regional differences in the green total factor productivity index of the service industry in the four regions of China as a whole. According to Dagum (1997), the Gini coefficient is defined as :

$$G = \frac{\Delta}{2\bar{Y}} = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji}-y_{hr}|}{2n^2\bar{y}} \qquad (4)$$

where Δ is the mean difference of the Gini coefficient. For example, for green total factor productivity, it is the average of the absolute value of every two production differences. Assuming that there are a total of n provinces, which can be divided into k subgroups (regions), n_j/n_h is the number of provinces in the j/h subgroup (region). y_{ji}/y_{jr} is the green total factor productivity the of service industry of any province (municipality directly under the Central Government, autonomous region) in the i/r subgroup (region), and $\bar{y}$ is the average value of green total factor productivity of service industry in all provinces in China.

Dagum (1997) gave a new subgroup decomposition method for the Gini coefficient, which can decompose the Gini coefficient into three parts: the contribution of intra-group gap G_w , the contribution of inter-group gap G_{nb} and the contribution of hyper variant density G_t . The relationship between the three satisfies the formula: $G = G_w + G_{nb} + G_t$. Before that decomposition of the Gini coefficient. First of all, according to the average value of green total factor productivity of the Service industry in each subgroup (region), each region is ranked $\bar{Y}_h \le \cdots \le \bar{Y}_j \le \cdots \le \bar{Y}_k$, where $\bar{Y}_j/\bar{Y}_h$ represents the average value of green total factor productivity of service industry in the j/h subgroup (region).

The formula group (5) describes the decomposition method and calculation method of Dagum in detail. G_{ij} and G_{jh} represent the intra-group Gini coefficient and the inter-group Gini coefficient, respectively. Δ_{jj} defines the average difference in Gini coefficients within j subgroups. In the same way, Δ_{jh} defines the average difference in the Gini coefficient between the j subgroup and the h subgroup.

$$P_j = n_j/n \ , s_j = n_j\bar{Y}_j/n\,\bar{Y}, j = 1,2,\dots,k$$

According to Dagum's (1997) definition of the concept of economic abundance D_{ij} is the relative degree of influence on the green efficiency of the service industry between the j and h subgroups. d_{jh} is defined as the difference in efficiency levels between the subgroups, which can be understood as the mathematical expectation of the sum of all which satisfies $y_{ji} - y_{hr} > 0$ sample values in the j and h subgroups. p_{jh} is defined as the hypervariable first-order distance, which can be understood as the mathematical expectation of the sum of all which satisfies $y_{hr} - y_{ji} > 0$ sample values in the j and h subgroups.

$$G_w = \sum_{j=1}^{J} G_{jj} p_j s_j$$

$$G_{jj} = \frac{\Delta_{jj}}{2\bar{Y}_j} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji} - y_{jr}|}{n_j^2}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right) D_{jh}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)\left(1 - D_{jh}\right)$$

$$G_{jh} = \frac{\Delta_{jh}}{\bar{Y}_j + \bar{Y}_h}$$

$$\Delta_{jh} = d_{jh} + p_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ji} - y_{hr}|}{n_j n_h} \qquad (5)$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}}$$

$$d_{jh} = \int_0^{\infty} dF_j(y) \int_0^{y} (y-x) d_{F_h(x)}$$

$$p_{jh} = \int_0^{\infty} dF_h(y) \int_0^{y} (y-x) d_{F_j(y)}$$

2.3. Spatial Markov chain

Markov chain method describes the dynamic evolution process of the green efficiency level of the service industry in various regions by constructing a Markov transfer matrix. Markov chain is a random process $\{X_t, t \in T\}$. Let the random variable $X_t = j$, namely the system state in the period be j. Its value is a finite set, and its spatial state is $I\{i, j \dots,\}$, and the Markov chain of the system satisfies formula (6), which suggests that the probability of the random variable X in the state in the period t+1 only depends on its state j in the period t.

$$P\{X_{t+1} = j | X_0 = i_0, X_1 = i_1, X_2 = i_2, \dots, X_{t-1} = i_{t-1}, X_t = i\} = P\{X_{t+1} = j | X_t = i\} = P_{ij} \quad (6)$$

Assuming that the green efficiency of a province's service industry shifts from the state t of year to the state t+1 of year, the maximum likelihood estimation method can be used: $P_{ij} = \frac{n_{ij}}{n_i}$, where n_{ij} means the number of all provinces that have transitioned from state i in year t to state j in year t+1 during the sample period, and n_i means to the number of all provinces in state i during the entire sample period.

Assuming a total of k States, a $k \times k$ transition probability matrix can be constructed. According to puetal. (2005), the efficiency level of a region will be affected by the efficiency level of adjacent regions, that is, the approximate value in random variables will have an aggregation effect in space. At present, there is little literature to study the interaction effect of green total factor productivity in spatial geography. We use the spatial Markov chain (Rey, 2001) method to introduce the concept of spatial lag to consider the impact of the efficiency level of adjacent provinces in each region on the efficiency level of the region in this period. Among them, the spatial lag value is the spatial weighting of the surrounding efficiency level of each province, and the calculation formula is as follows:

$$F_r = \sum w_{sr} y_s \quad (s \neq r) \qquad (7)$$

Where F_r is the spatial lag value of province r, and y_r is the productivity value of province s. w_{sr} is a spatial weight matrix, if province s borders province r, then $w_{sr} = 1$, otherwise, $w_{sr} = 0$.

3. Data

In this paper, the research area is 30 provinces, municipalities, and autonomous regions in China (excluding Tibet). According to the geographical division of China by the National Bureau of statistics in 2011, it is divided into four regions, namely the East, northeast, central, and West. In this paper, the labor force, capital stock and energy consumption of the service industry are selected as the input indicators, the added value of the tertiary industry as the expected output, and carbon dioxide, sulfur dioxide, and chemical oxygen demand (COD) as the unexpected output. Some missing data are calculated and supplemented according to the interpolation method. The calculation method is mainly based on Pang and Deng (2014), Wang et al. (2015).

(1) Labor force. Human capital plays a vital role in economic growth. Fuchs believes that due to the volatility of service demand, the actual working hours invested in the service sector are less than those in the industrial sector, that is, the per capita working hours in the service sector is less than those in the industrial sector. In addition, there is heterogeneity in labor input in various industries of the service industry, so labor input in the model should take into account both labor quantity and labor time. In this paper, the labor input index is set as the number of employees in each sub-industryof the tertiary industry multiplied by the average working hours of employees in each sub-industry.

(2) Capital input. This paper uses the "sustainable inventory method" to estimate the actual capital stock of each province, city, and autonomous region every year. The calculation method is:$K_{i,t} = I_{i,t} + (1-\delta)K_{i,t-1}$. Where $K_{i,t}$ and $K_{i,t-1}$ are the capital stock of area i in year t and t+1 respectively, $I_{i,t}$ is the investment in area i in year t, and Sigma is the depreciation rate of fixed assets.

(3) Energy input. Select the indicator of the total terminal energy consumption of the service industry in each province, city, and autonomous region. The unit of energy consumption is 10000 tons of standard coal, which is converted into standard coal according to the conversion coefficient of different energy.

(4) Expected output. Select the added value of the service industry of each province as the only good output index, and flatten it through the added value index of the tertiary industry.

(5) Unexpected output. ① The main component of greenhouse gas is CO2, and CO2 emission cannot be obtained directly, so it needs to be estimated. According to the reference method provided by the guidelines for greenhouse gas inventories formulated by the United Nations Intergovernmental Panel on climate change (IPCC), CO2 emissions are converted from the carbon emission coefficients of various different energy sources in the energy statistics yearbook. ② Pollutant SO2. The SO2 emission of provinces and cities can be obtained from China Statistical Yearbook 2012-2020. Its statistics include industrial sulfur dioxide and domestic sulfur dioxide. Referring to the existing literature, this paper selects domestic sulfur dioxide and further converts it into sulfur dioxide emitted by the service industry. The calculation method is to multiply the domestic sulfur dioxide emission by the proportion of employees in tertiary industry urban units in the regional permanent population. ③ The calculation method of COD and sulfur dioxide pollution emission is the same.

4. Empirical Analysis

4.1. Analysis of green efficiency of China's inter-provincial service industry

This paper uses a global integration model to estimate the green efficiency level of the service industry in China's 30 provinces from 2011 to 2019 based on variable returns to scale. As shown in Table 1, in 2011, 7 provinces reached a relatively effective level (efficiency level greater than 1), but there are also 15 provinces that have low green efficiency levels (efficiency level less than 0.5). Although the country is developing on the positive side, 7 provinces have green efficiency levels greater than 1.0 in 2019, but there are still 20 provinces with green efficiency levels below 0.5 in the service industry, most of which are located in central, western and northeastern China. Therefore, we can infer that, based on the degree of willingness and investment strength of each province to improve the green efficiency of the service industry, the efficiency gap between provinces has a tendency to increase. Focusing on the eastern part of China, 60% of eastern China's provinces reached relatively effective (efficiency value greater than 1) as early as 2011, indicating that 60% of eastern provinces were already at the frontier of efficiency in 2011. Throughout the study period, the efficiency of Beijing, Tianjin, Shanghai, Zhejiang, and Jiangsu has been very high, basically above 1.0. Among them, Hebei, Fujian, Shandong, and Guangdong have shown fluctuations in the green efficiency of the service industry as time evolves. The situation is constantly approaching the frontier of efficiency. In particular, the high green efficiency of Hainan's service industry may be due to errors in Hainan's service industry energy consumption statistics. The higher green efficiency of the service industry in western inland areas such as Ningxia may be due to the underdeveloped service industry in the region, the smaller scale of input and output, and more small-scale service industries that are statistically biased and produce less undesired output.

Table 1. Green efficiency level of the service industry in China's 30 provinces from 2011 to 2019

Area	Province	2011	2012	2013	2014	2015	2016	2017	2018	2019
East	Beijing	1.073	1.073	1.124	1.129	1.122	1.089	1.126	1.045	1.080
	Tianjin	1.052	1.080	1.096	1.062	1.072	1.041	1.002	0.447	0.394
	Hebei	0.335	0.342	0.275	0.246	0.229	0.239	0.221	0.236	0.207
	Shanghai	1.060	1.053	1.014	1.033	1.058	1.187	1.457	1.268	1.229
	Jiangsu	1.055	1.056	1.077	1.171	1.167	1.265	1.474	1.414	1.232
	Zhejiang	1.016	1.025	1.026	1.035	1.023	0.665	1.027	1.041	1.024
	Fujian	0.433	0.434	0.554	0.620	0.671	0.450	0.469	0.464	0.433
	Shandong	0.353	0.365	0.428	0.430	0.345	1.006	1.003	0.368	0.416
	Guangdong	1.105	1.081	1.084	1.080	1.100	1.075	1.079	1.072	1.060
	Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Northeast	Liaoning	0.279	0.264	0.257	0.241	0.279	0.296	0.374	0.341	0.295
	Jilin	0.294	0.295	0.265	0.282	0.285	0.276	0.273	0.258	0.227
	Heilongjiang	0.188	0.154	0.135	0.137	0.143	0.133	0.136	0.103	0.105
West	Inner Mogolia	0.362	0.336	0.262	0.257	0.257	0.301	0.320	1.002	0.316
	Guangxi	0.348	0.373	0.555	0.529	0.587	1.000	1.000	1.000	1.000
	Chongqing	0.437	0.467	0.446	0.543	0.538	1.000	1.000	1.000	1.000
	Sichuan	0.278	0.295	0.242	0.282	0.295	0.337	0.351	0.361	0.219
	Guizhou	0.347	0.331	0.256	0.235	0.234	0.210	0.202	0.195	0.174
	Yunnan	0.476	0.435	0.367	0.344	0.350	0.338	0.321	0.362	0.316
	Shaanxi	0.315	0.415	0.393	0.370	0.357	0.507	0.445	0.388	0.307
	Gansu	1.000	1.000	0.378	0.348	0.333	0.310	0.299	0.329	0.283
	Qinghai	1.370	1.215	1.188	1.236	1.345	1.258	1.312	1.179	1.120
	Ningxia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Xinjiang	0.617	0.568	0.430	0.400	0.357	0.292	0.299	0.330	0.269
Centre	Shanxi	0.328	0.338	0.311	0.302	0.341	0.315	0.349	0.433	0.343
	Anhui	0.344	0.350	0.274	0.282	0.286	0.281	0.281	0.402	0.361
	Jiangxi	0.509	0.517	0.534	0.544	0.576	0.364	0.345	0.367	0.324
	Henan	1.000	0.481	0.348	0.330	0.318	0.334	0.369	0.381	0.352
	Hubei	0.325	0.316	0.316	0.323	0.317	0.298	0.293	0.313	0.270
	Hunan	0.358	0.336	0.262	0.269	0.270	0.264	0.251	0.227	0.231

As shown in Figure 2, from a regional perspective, compared with the other three regions, eastern China has maintained a higher average green efficiency in the service industry. Thanks to years of reform and opening up policies, it has promoted the development of many industries. Including the service sector, the eastern service sector developed earlier and has a larger scale. During the sample period, the service industry in the eastern region had the highest green efficiency, followed by the western region, and the northeast region had the lowest green efficiency. The western region has relatively high green efficiency due to the slow development of the service industry and insufficient production capacity and output. In the central and northeastern regions, the service industry has begun to see scale, but due to the limited technological level, there may be a high investment and low expected output. The dilemma of high undesired output.

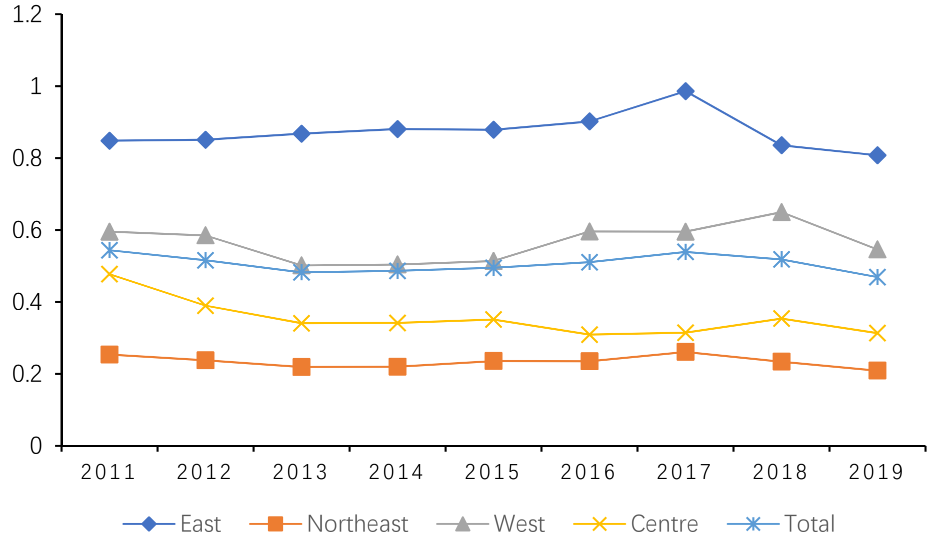


Figure 2. Regional differences in green efficiency of China's service industry

Specifically: During the period from 2011 to 2019, the overall green efficiency of the service industry in most provinces in China has improved, especially in the eastern and western regions of China, but there is a downward trend from 2017 to 2019. It seems that the eastern region is better than the western, central, and northeastern regions. The overall green efficiency of the eastern region is above 0.8, and the central and northeastern regions are still relatively low during the 2011-2019 period, at an efficiency level below 0.5. In contrast, the green efficiency of the service industry in most regions has only slightly improved during the period 2011-2019, but the overall situation has fluctuated slightly and has become a relatively stable state.

4.2. Regional differences and decomposition of green efficiency in the service industry

It can be seen from the above that there are differences between different regions. In order to find the main source of regional differences in green efficiency in China’s service industry, we use the Gini coefficient and decomposition method proposed by Dagum (1997) to divide China’s 30 provinces into The eastern, central, western, and northeastern regions were decomposed, and the Gini coefficient of the green efficiency of China's service industry from 2011 to 2019 was calculated. The calculation results are shown in Table 2. The following are the basic characteristics of the green efficiency gap in China's service industry.

Table 2. Dagum Gini coefficient and decomposition results of green efficiency service industry

	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Total	0.318	0.302	0.311	0.321	0.328	0.346	0.379	0.346	0.336	0.332
East	0.175	0.172	0.174	0.180	0.186	0.192	0.219	0.250	0.232	0.194
Northeast	0.101	0.134	0.124	0.138	0.135	0.155	0.226	0.226	0.181	0.155
West	0.316	0.284	0.257	0.269	0.287	0.343	0.349	0.337	0.336	0.305
Centre	0.308	0.114	0.124	0.121	0.133	0.053	0.066	0.103	0.072	0.128
E/N	0.537	0.554	0.586	0.599	0.587	0.608	0.667	0.551	0.547	0.586
E/W	0.306	0.292	0.331	0.345	0.356	0.329	0.375	0.310	0.327	0.331
E/C	0.365	0.395	0.443	0.458	0.456	0.494	0.562	0.415	0.420	0.448
N/W	0.429	0.435	0.357	0.361	0.359	0.463	0.458	0.538	0.444	0.425
N/C	0.380	0.258	0.208	0.209	0.201	0.137	0.163	0.236	0.194	0.224
W/C	0.332	0.275	0.248	0.251	0.262	0.344	0.346	0.381	0.330	0.305
Gw	0.242	0.225	0.209	0.210	0.217	0.223	0.219	0.253	0.249	0.225
Gnb	0.536	0.637	0.685	0.677	0.646	0.658	0.671	0.557	0.584	0.633
Gt	0.221	0.138	0.106	0.113	0.137	0.119	0.110	0.190	0.167	0.142

Note: "E", "N", "W" and "C" refer to the East, northeast, West and central regions of China. The unit of contribution rate is %.

①The overall regional gap in green efficiency of China's service industry. It can be seen from the data in Figure 3 that the overall Gini coefficient of green efficiency in China's service industry has risen from 0.318 to 0.336, with an average value of 0.332. It shows that the spatial difference in green efficiency in China's service industry is expanding. From the perspective of changing trends, the green efficiency of China's service industry has generally increased between 2011 and 2017. After 2018, the green efficiency decreased, but the magnitude is not large. Compared with 2011, the overall gap has narrowed by 12.9% in 2019, with an average annual decrease of 0.9%. This shows that although the overall difference in green efficiency in China's service industry is not very significant, with the country's emphasis on carbon emissions in recent years, the importance and economic focus of different regions are different, leading to the further expansion of regional differences.

② Intra-group differences in green efficiency of China's service industry. The intra- group differences in the four regions of China show different trends. As can be seen from Figure 3, from the perspective of the degree of differentiation, the western region has the largest degree of intra-cluster differentiation (the average value of the intra-cluster Gini coefficient in the western region during the sample period is 0.305), while the eastern and central regions have relatively small intra-regional differentiation. (The average values of the intra-regional Gini coefficients in the eastern and central regions during the sample period were 0.194 and 0.155). The degree of intra-cluster differentiation in the Northeast is the smallest (the average value of the intra-cluster Gini coefficient in the western region during the sample period is 0.128). From the perspective of changing trends, the western and northeastern regions have roughly the same changing trends. The Gini coefficients of these two regions and the whole country are roughly the same. The Gini coefficients of the eastern region have increased in a small range, and the overall trend is relatively stable. The changing trend of the Gini coefficient in the central region is unstable, but the general trend is that the degree of differentiation is shrinking.

The above results show that China's service industry's green efficiency has obvious spatial differentiation characteristics. During the entire inspection period, the regional differentiation of service industry green efficiency in the central region showed a gradual shrinking trend (the Gini coefficient within the regional group has been reduced from 0.318 in 2011). It fell to 0.072 in 2019), while the spatial differentiation of green efficiency in the service industry in the northeast and western regions showed an expanding trend (the Gini coefficient rose from the lowest 0.257 and 0.101 to the highest 0.226 and 0.349, respectively). Specifically, some provinces in Northeast and Western China are committed to improving the green efficiency of the local service industry, such as Liaoning, Chongqing, and Guangxi, and they have achieved significant results. However, in some provinces, such as Heilongjiang, Gansu, Yunnan, and Guizhou, the green efficiency of the service industry has declined since 2011. The different scales of the service industry in each region, the different policies promoted, and the importance of each region on the green efficiency of the service industry may all be the reasons for the difference in their final efficiency levels. This has also widened the gap in the green efficiency of the service industry in the northeast and western regions of China. In particular, the gap within the group in western China has become very obvious, mainly because the green efficiency of the service industry in Gansu, Yunnan, and Guizhou did not increase during the study period, but declined, making the gap widen.

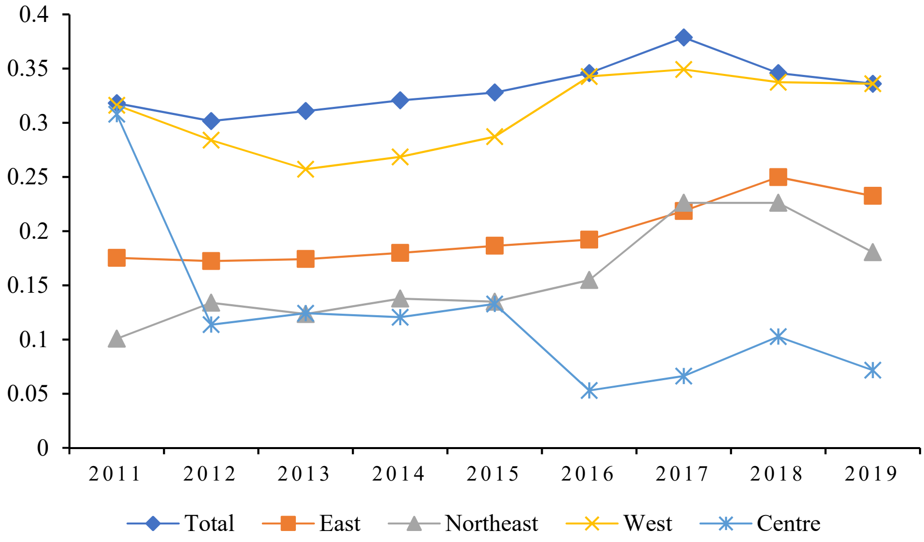
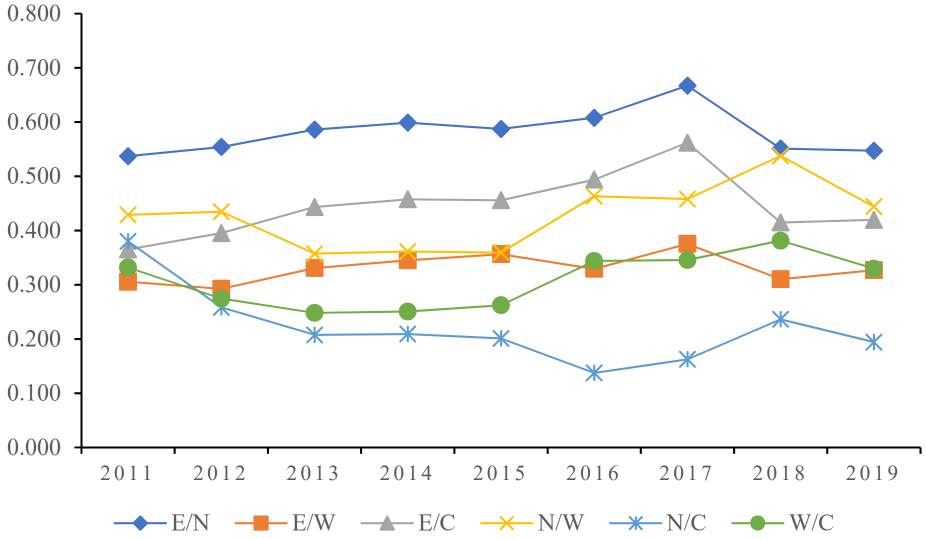


Figure 3. Intra-group differences in green efficiency of China's service industry

③ Inter-group differences in green efficiency of China's service industry. On the whole, the average value of the inter-group difference in green efficiency of China's service industry is 0.386 (see Figure 4). Among them, the average value of the inter-cluster difference between eastern and northeastern China is the highest (the average value of the Gini coefficient between eastern and central regions during the sample period is 0.586), and the degree of inter-cluster differentiation between northeastern and central, eastern and western, and western and central It is the inter-cluster difference value lower than China's overall efficiency difference level (0.386) (the average Gini coefficient between the eastern and central regions during the sample period was 0.224, 0.331, and 0.305, respectively). The degree of inter-cluster differentiation between eastern and central China, and western and northeastern China (the average Gini coefficient between eastern and central regions during the sample period was 0.448 and 0.425, respectively) is higher than the overall efficiency difference in China (0.386). In terms of trends, the inter-cluster differences between central and northeastern China, and between eastern and northeastern China decreased by 31.01% and 27.31%, respectively, during the sample period. The differences between groups in the eastern and western regions also decreased, but the degree was not as great as the former two, with a decrease rate of 11.19%. Before 2017, the difference between the east and the northeast reached the largest (the Gini coefficient between the east and the northeast was 0.667). It can be seen from Figure 4 that the differences between groups are different, and it also reflects that the development of various regions is uneven, and some regions are developing faster in a good direction.



Figur 4. Group differences in green efficiency of China's service industry

④ Regional differences and contributions of green efficiency in China's service industry. Figure 5 depicts the source of regional differences in green efficiency in China's service industry and the magnitude of its contribution rate. We found that the main source of disparity is the difference between regions (between groups). During the sample period, the contribution rate was around 60%. The average contribution rate of the difference between the groups was 63.33%, and the average contribution rate of the difference within the group was 22.55. %, the average contribution rate of differences between groups is more than twice that of differences within groups. This shows that inter-group differences are the main source of overall regional differences in green efficiency in China's service industry, and reducing inter-group differences is the key to solving the problem of regional imbalances in China's carbon emission efficiency. From 2011 to 2019, the three sources of difference have shown a small-scale downward trend. The contribution rate of intra-group difference decreases by 0.807% annually, the contribution rate of inter-group difference decreases by 0.517% annually, and the annual average contribution rate of hypervariable density Decrease by 0.01%. In addition, the contribution rate of hypervariable density reveals the impact of cross-term statistics among the four regions of China on the overall efficiency difference, reflecting the interaction between group differences and intra-group differences on the overall efficiency gap Contribution rate. The changing trend of the contribution rate of the hypervariable density shows that the interactive effects of intra-group differences and inter-group differences are gradually weakening, but the overall change is not obvious.

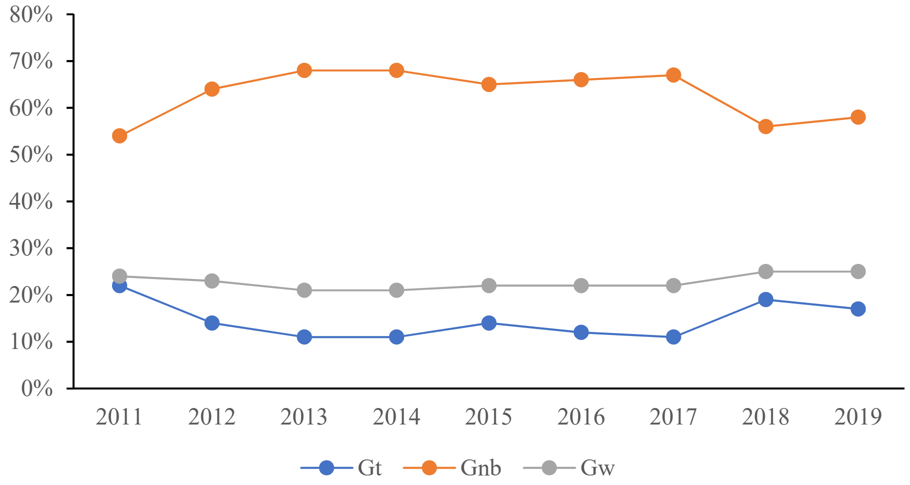


Figure 5. Source and contribution rate of green efficiency difference

4.3. Spatial analysis of the status transition of green efficiency in China's service industry

In order to study the dynamic transfer characteristics of the green efficiency of the service industry in 30 provinces in China for 9 years, this section uses the traditional Markov chain and the spatial Markov chain method. According to the level of green efficiency in the service industry, each province is divided into five types: (1) The efficiency value is less than 0.30; (2) The efficiency value is between 0.30 and 0.40; (3) The efficiency value is between 0.40 and 0.75; (4) The efficiency value is between 0.75 and 1.00; (5) The efficiency value is higher than 1.00. These five types are represented as low-efficiency provinces (VL), low- and medium-efficiency provinces (L), medium-efficiency provinces (M), medium-high-efficiency provinces (H), and high-efficiency provinces (VH), as shown in table 3 shown.

Table 3. Grouping of green efficiency of service industry in 30 provinces of China

	VL	L	M	H	VH
Green efficiency value	<=0.30	0.30~0.40	0.40~0.75	0.75~1.00	1.00 ~1.5
Numbers	68	72	38	29	63

Table 4 shows the maximum likelihood estimation of the transition probability of green efficiency in China's service industry. The elements of the main diagonal represent the probability that a province maintains its initial state unchanged, that is, the efficiency level in the next period does not increase or decrease. The elements outside the main diagonal represent the probability of a province transitioning from its current state to another state in the next period.

Table 4. Markov chain transition probability matrix of green efficiency (2011-2019)

t/t+1	n_i	VL	L	M	H	VH
VL	68	0.897	0.086	0.017	0.000	0.000
L	72	0.188	0.688	0.094	0.000	0.031
M	38	0.000	0.278	0.639	0.083	0.000
H	29	0.000	0.040	0.040	0.880	0.040
VH	63	0.000	0.035	0.035	0.000	0.930

First, the transition probability on the main diagonal is relatively high. The provinces with low and high-efficiency levels of green efficiency in the service industry have the highest probability of maintaining the original level, 89.7%, and 93.0% respectively. The polarization is more serious. The probability that other provinces with efficiency levels remain unchanged is also above 65%. This shows that the relative position of the overall green efficiency level of the service industry in each region is relatively stable, and most provinces have remained at the original efficiency level. Second, the transition probabilities of off-diagonal lines are not all zero, and they are basically distributed on both sides of the diagonal line. This shows that some provinces may realize the transition of green efficiency in the service industry to adjacent levels within two consecutive years. Among them, the possibility of realizing the transition of efficiency level is very low. For example, the probability of a transition from a province with a low-efficiency level to a higher level of efficiency is only 8.6%, and the probability of a transition from medium to medium to high is 8.3%. Fourth, the probability of shifting upward and downward on the off-diagonal line is asymmetric. In other words, the probability that the efficiency level of each region will decline in the next year is much higher than the probability that it will increase. In particular, the probability of upward transition and downward transition at a medium-to-high level is equal, indicating that the medium-high efficiency level has the same probability of efficiency improvement and reduction.

The above-mentioned research results show that Chinese provinces have made corresponding efforts in improving the green efficiency of the service industry in recent years, and have achieved certain results. However, the traditional Markov chain does not consider the spatial interaction between regions, so it cannot explain the spatial mechanism that causes the convergence or divergence of regional efficiency (Puetal. 2005).

Table 5 is the spatial Markov chain transfer matrix considering the spatial lag effect, exploring the impact of the efficiency environment of neighboring provinces on the green efficiency of the regional service industry. The specific features are as follows.

1. The green efficiency of China's service industry is affected by the neighboring environment. Similar to the traditional Markov chain, in the spatial Markov chain matrix, the element values on the main diagonal are greater than those on the off-diagonal lines in the context of various fields, which also shows that the green efficiency of China's service industry has greater club stability. It can be seen from Table 6 that when the neighborhood is at a high-efficiency level, the impact on an area is most significant. In the case of high-efficiency samples, these samples will not shift to low levels. When the neighborhood is at a high efficiency level, the samples are clustered at a medium-high or high-efficiency level, and the samples are not transferred. When the neighborhood is at a low-efficiency level, the probability of a low-efficiency level shifting upward is 11.8%, the probability of a medium-low efficiency shifting downward is 22.2%, and the probability of a medium-high efficiency level to a medium-low efficiency level is 33.3%, and cross-regional transfer and the probability of the higher efficiency level shifting downward is 0.

2. When the neighborhood is in the first four types of efficiency levels, we find that with the improvement of the efficiency level of the neighborhood, the probability of upward transfer of the area will basically increase. For example, when the neighboring provinces of a region are at a medium efficiency level, the probability that the region maintains a medium efficiency level is as high as 50%. As the green efficiency of the service industry in the neighborhood goes from low to medium-high, the probability that the region will increase to a high efficiency level rises from 16.7% to 25%. This shows that the green efficiency of the regional service industry is affected to a certain extent by the efficiency of neighboring provinces.

3. Different neighborhoods have different transfer effects on samples. Taking a province with a high efficiency level as an example, when the neighborhood is a high-efficiency and a medium-high efficiency level, the sample will not transfer to a low-efficiency level; when the neighborhood is a province with a medium-efficiency level and a medium-low efficiency level, the sample may move to Medium-high and medium-efficiency levels transfer, but the probability is also

very small; when the field is a province with a low-efficiency level, the province with a high efficiency level will transfer to a medium-high level, but in general, the probability is very small. The province has developed to a high level of efficiency, and the reversal is minimal.

Table 5. Spatial Markov chain transition probability matrix of green efficiency (2011-2019)

	t/t+1	n_i	VL	L	M	H	VH
VL	VL	17	0.882	0.118	0.000	0.000	0.000
	L	9	0.222	0.778	0.000	0.000	0.000
	M	3	0.000	0.000	0.667	0.333	0.000
	H	3	0.000	0.333	0.000	0.667	0.000
	VH	1	0.000	0.000	0.000	0.000	1.000
L	VL	7	0.857	0.143	0.000	0.000	0.000
	L	16	0.125	0.750	0.063	0.000	0.063
	M	5	0.000	0.400	0.600	0.000	0.000
	H	3	0.000	0.000	0.333	0.667	0.000
	VH	7	0.000	0.143	0.000	0.000	0.857
M	VL	31	0.935	0.065	0.000	0.000	0.000
	L	36	0.194	0.639	0.139	0.000	0.028
	M	18	0.000	0.389	0.500	0.056	0.056
	H	3	0.000	0.000	0.000	1.000	0.000
	VH	29	0.000	0.034	0.034	0.000	0.931
H	VL	3	0.333	0.333	0.333	0.000	0.000
	L	3	0.667	0.333	0.000	0.000	0.000
	M	8	0.000	0.125	0.875	0.000	0.000
	H	6	0.000	0.000	0.000	1.000	0.000
	VH	13	0.000	0.000	0.077	0.000	0.923
VH	VL	0	0.000	0.000	0.000	0.000	0.000
VH	L	0	0.000	0.000	0.000	0.000	0.000
	M	2	0.000	0.000	1.000	0.000	0.000
	H	10	0.000	0.000	0.000	1.000	0.000
	VH	7	0.000	0.000	0.000	0.000	1.000

4. The difference between the transition probability matrix of the traditional Markov chain and the spatial Markov chain. For a province with a low-efficiency level, without considering the spatial effect, the probability that it will be improved in the next year is 10.3%. But if its neighboring provinces are at a lower efficiency level, the transition probability will rise to 11.8%, and as the efficiency level of the neighboring provinces rises to a low-medium level, the transition probability will also increase to 14.3%. Therefore, the traditional Markov chain only gives an average transition probability value, while the spatial Markov chain can reflect the degree of transition direction and transition probability affected by spatial geographic factors and the level of neighborhood efficiency.

5. Conclusion and Implications

This paper uses the integrated SBM-DDF model and super efficiency SBM-DDF model to calculate the green efficiency of the service industry in 30 provinces, cities, and autonomous regions in China during 2011-2019, Using the subgroup decomposition method of dagum Gini coefficient and the spatial Markov Chain Considering the lag value of adjacent regions, this paper analyzes the regional differences and spatial dynamic evolution of green efficiency of service industry in four regions of China and draws the following four conclusions.

(1) During the investigation period, the green efficiency of the service industry in four regions of China has a steady upward trend. Compared with the other three regions, Eastern China has maintained a higher average green efficiency in the service industry. Thanks to the policies of reform and opening up for many years, it has promoted the development of many industries, including the service sector. The service industry in eastern China developed earlier and on a larger scale. In the whole sample period, the green efficiency of the service industry in the eastern region is the highest, followed by the western region, and the northeast region is the lowest. Due to the slow development of the service industry and insufficient production capacity and output in the western region, its green efficiency is also relatively high. In the central and northeast regions, the service industry has begun to take shape, but due to the limited technical level, there may be a dilemma of high input, low expected output, and high unexpected output.

(2) The overall Gini coefficient of green efficiency of China's service industry fluctuated slightly from 2011 to 2019, showing a slightly expanding trend as a whole. The average value is 0.386, which is mainly due to the expansion of the differences between groups, resulting in the increase of the Gini coefficient in the whole region, and the imbalance of regional development tends to increase. At the same time, the green efficiency of China's service industry has obvious spatial differentiation characteristics. During the whole investigation period, the regional differentiation of green efficiency of the service industry in the central region shows a gradually narrowing trend. In terms of regions, the intra-group difference of efficiency in the eastern region decreased significantly, from the second position of intra-group gap to the region with the smallest gap. The reason is that the eastern region is most significantly affected by the reform and opening up. The economy has developed rapidly and the level of urbanization is high. According to the needs of social

development, the tertiary industry has risen rapidly in the eastern region in recent years, so there is no significant difference in the green efficiency level of the service industry.

(3) The inter-group differences among the four regions are the main source of the regional differences in the green efficiency of China's service industry. Among them, the intergroup differences between eastern and Northeast China, Eastern and central China decreased significantly, the intergroup differences between eastern and Western China decreased slightly in fluctuation, and only the intergroup differences between Northeast and Western China increased. The differences between each region are different, which shows that the economic development level, technology introduction and promotion degree of the service industry in each region lead to the imbalance of green efficiency level of the service industry in each region.

(4) From the traditional Markov chain, we can know that the probability of most provinces transferring to the high efficiency level will be greater than that to the low-efficiency level, and the probability of provinces reaching the high efficiency level remaining at this efficiency level is 93.1%. This shows that in recent years, with the national attention to carbon emissions, the efficiency level of all regions has generally improved steadily, and most of the provinces that have reached the high efficiency level will maintain the status quo. In addition, the green efficiency level of the service industry in China's provinces presents obvious space. Dependence is significantly affected by the efficiency level of adjacent provinces. Neighboring provinces with high efficiency levels have a positive radiation effect on the green efficiency of the service industry in surrounding provinces while neighboring provinces with low-efficiency level will have a certain inhibitory effect.

According to the above conclusions, at present, there is an obvious spatial imbalance in the green efficiency of China's service industry, especially in the central and northeast regions. Although the gap between the central and northeast regions and the eastern region has expanded in the past nine years, it has not changed much. The existence of these problems requires local governments to formulate corresponding policies according to their own development and their current situation.

To develop itself, all regions, especially the central and northeastern regions, must be guided by "high efficiency, high quality, and high quality" to accelerate the transformation and upgrading of the service economy development model. Formulate differentiated development strategies. The central and northeast regions with low efficiency should develop new service industries such as the digital economy and change the mode of high energy consumption and high unexpected output of traditional service industries. In traditional service industries, transportation, warehousing, and other service industries need to consume a lot of energy and produce corresponding unexpected output at the same time. Therefore, the corresponding proportion of traditional service industries should be reduced, Develop new service industries such as the digital economy. Formulate more regionally targeted environmental protection policies, so as to combine with the cross-regional joint prevention and treatment system of environmental pollution, and finally realize the purpose of ecological civilization construction of resource conservation, environmental protection, and sustainable development of service industry。

Establish multilateral or bilateral regular exchange mechanisms, focus on improving regional differences in green efficiency of the service industry, strengthen technical cooperation, and provide "one-to-one" assistance to provinces with high green efficiency and low efficiency. Because the green efficiency of the service industry in the western region is low and different from other regions, we should pay special attention to it. Find out the fundamental factors for the low green efficiency of the service industry in the central, western and northeast regions, reduce the emissions of carbon dioxide, sulfur dioxide, and chemical oxygen demand according to the actual situation of western development and in combination with the local climate and terrain characteristics, and strengthen the technological innovation cooperation and exchange among regions and provinces, so as to drive the central, Western and The overall green efficiency of service industry in Northeast China is increasing, so as to explore the appropriate ways for the development of green service industry with the characteristics of central, Western and Northeast China.

References

[1] Atakelty S. Veeman. Environmentally Sensitive Productivity Analysis of the Canadian Pulp and Paper Industry, 1959-1994: An Input Distance Function Approach[J]. Journal of Environmental Economics and Management, 2000,40(3):

[2] Alcántara V., Padilla E. Input-output Subsystems and Pollution: An Application to the Service Sec- tor and CO2 Emissions in Spain [J]. Ecological Economics, 2009,68(3).

[3] Bing.W, Yanrui.W, Pengfei.Y. Regional Environmental Efficiency and Environmental Total Factor Productivity Growth in China [J]. Economic Research Journal, 2010,45(05).

[4] Chung Y. H., Fare R., Grosskopf S. Productivity and Undesirable Outputs: A Directional Dis- tance Function Approach [J]. Journal of Environmental Management, 1997, 51(3).

[5] Chen S. Y., Golley J. Green Productivity Growth in China’s Industrial Economy[J]. Energy Economics, 2014,44.

[6] Dong-hyun Oh. A global Malmquist-Luenberger productivity index[J]. Journal of Productivity Analysis, 2010,34(3).

[7] Dagum C. A New Approach to the Decomposition of the Gini Income Inequality Ratio [J]. Physica-Verlag HD, 1998.

[8] Tran T H, Mao Y, Nathanail P, et al. Integrating Slacks-based Measure of Efficiency and Super-efficiency in Data Envelopment Analysis [J]. Omega, 2018, 85(1).

[9] Hailu A., Veeman T. S. Environmentally Sensitive Productivity Analysis of the Canadian Pulp and Paper Industry, 1959 ~ 1994: An Input Distance Function Approach [J]. Journal of Environmental Economics and Management, 2000, 40(3).

[10] Hirofumi Fukuyama, William L. Weber. A Directional Slacks-based Measure of Technical Inefficiency [J]. Socio-Economic Planning Sciences, 2008,43(4).

[11] Hoang V., Coelli T. Measurement of Agricultural Total Factor Productivity Growth Incorporating Environmental Factors: A Nutrients Balance Approach [J]. Journal of Environmental Economics and Management, 2011,62(3).

[12] Hui.M, Lin.L, Xiaofen.X. Research on Structural Differences and Influencing Factors of Green Development of China's Service Industry -- Green Technology Efficiency Measurement Based on Bootstrap DEA Model [J]. Economic Review Journal, 2021(06).

[13] Jinghua.C, Susu.W. Spatial Differences and Influencing Factors of Green Total Factor Productivity Growth in China's

Service Industry [J]. Journal of Nanjing University of Finance and Economics, 2020,(02).

[14] Jinghua.C. Convergence Analysis of Green Total Factor Productivity Growth in China's Service Industry -- a Test from the Perspective of Industry Heterogeneity [J]. Soft Science, 2020, 34(04).

[15] Jianglong.L, Bing.X. Curse or Gospel: How Does Resource Abundance Affect China's Green Economic Growth? [J]. Economic Research Journal, 2018,53(09).

[16] Kumar S. Environmentally Sensitive Productivity Growth: A Global Analysis Using Malmquist-Luenberger Index [J]. Ecological Economics, 2006,56(2).

[17] Lawrence M. Seiford,Joe Zhu. A Response to Comments on Modeling Undesirable Factors in Efficiency Evaluation[J]. European Journal of Operational Research, 2003,161(2).

[18] Longzheng.D, Yunhui.Z, Ketao.T, Weifen. L. The Compound Effect of Environmental Regulation and Governance Transformation on the Promotion of Green Competitiveness -- Based on the Empirical Evidence of Chinese Industry [J]. Economic Research Journal, 2019,54(10).

[19] Nanere Marthin, Fraser Iain, Quazi Ali, D'Souza Clare. Environmentally Adjusted Productivity Measurement: an Australian Case Study [J]. Journal of environmental management, 2007,85(2).

[20] Nanere M., Fraser J., Quazi A., D'Souza C. Environmentally Adjusted Productivity Measure- ment: An Australian Case Study [J]. Journal of Environmental Management, 2007,85(2).

[21] Oh D. A Global Malmquist Luenberger Productivity Index [J]. Journal of Productivity Analysis, 2010,34(3).

[22] Ruizhi.P, Zhongqi.D. Is the Production Rate of Service Industry Really Low? [J]. Economic Research Journal, 2014, 49(12).

[23] Sergio J. Rey. Spatial Empirics for Economic Growth and Convergence [J]. Geographical Analysis, 2001,33(3).

[24] Surender Kumar. Environmentally Sensitive Productivity Growth: A Global Analysis Using Malmquist–Luenberger Index [J]. Ecological Economics, 2005,56(2).

[25] Seiford L. M., Zhu J. A Response to Comments on Modeling Undesirable Factors in Efficiency E- valuation [J]. European Journal of Operational Research, 2005,161(2).

[26] Shuai.L. Regional Differences and Stochastic Convergence of China's Economic Growth Quality [J]. The Journal of Quantitative & Technical Economics, 2019,36(09).

[27] Shuli.W, Xuliang.W. Does FDI in service industry improve green Total Factor Productivity -- An Empirical Study Based on China's Inter-provincial Panel Data [J]. Journal of International Trade, 2017,(12).

[28] Shuli.W, Zewei.T, Jun.L. Analysis on the Difference of Productivity Change in China's Service Industry -- from the Perspective of Region and Industry [J]. Economic Research Journal, 2015,50(08).

[29] Trung Hieu Tran, Yong Mao, Paul Nathanail, Peer-Olaf Siebers, Darren Robinson. Integrating Slacks-based Measure of Efficiency and Super-efficiency in Data Envelopment Analysis [J]. Omega, 2019,85.

[30] Viet-Ngu Hoang, Tim Coelli. Measurement of Agricultural Total Factor Productivity Growth Incorporating Environmental Factors: A Nutrients Balance Approach[J]. Journal of Environmental Economics and Management, 2011,62(3).

[31] Vicent Alcántara, Emilio Padilla. Input–output Subsystems and Pollution: An Application to the Service Sector and CO 2 Emissions in Spain [J]. Ecological Economics, 2008,68(3).

[32] Xuliang.W, Shuli.W, Zewei.T. Spatial Convergence of Carbon Productivity in China's Service Industry [J]. China Population, Resources and Environment, 2020,30(02).

[33] Xuliang.W. Market Segmentation, Spatial Interaction and Influencing Factors of China's Service Products [J]. The Journal of Quantitative & Technical Economics, 2020,37(02).

[34] Xuliang.W, Shuli.W. Green Productivity Effect of China's Service Industry Agglomeration [J]. Journal of Shanxi University of Finance and Economics, 2021,43(03).

[35] Xuliang.W, Han.X. Recalculation and Spatial Convergence of Green TFP in China's Service Industry [J]. Journal of Statistics, 2020,1(05).

[36] Y.H. Chung, R. Färe, S. Grosskopf. Productivity and Undesirable Outputs: A Directional Distance Function Approach [J]. Journal of Environmental Management, 1997, 51(3).

[37] Yu M. M., Hsu S. H., Chang C. C., Lee D. H. Productivity Growth of Taiwan's Major Domestic Airports in the Presence of Aircraft Noise [J]. Transportation Research Part E: Logistics and Transportation Review ,2008,44(3).

[38] Ying-Xia P U, Rong-Hua M A, Ying G E, et al. Spatial-temporal Dynamics of Reginal Convergence at County Level in Jiangsu [J]. Chinese Geographical Science, 2005,15(2).

[39] Ying.H, Liping.M. Research on Total Factor Productivity in the Change of Industrial Structure in Beijing, Tianjin and Hebei [J]. The Journal of Quantitative & Technical Economics, 2019, 36(06).

[40] Zewei.T. Spatial Differentiation and Driving Factors of Green Total Factor Productivity in China's Service Industry [J]. The Journal of Quantitative & Technical Economics, 2020,37(11).

[41] Zewei.T, Zongbiaao. H,Xiyan.J. Study on the Difference and Convergence of Carbon Productivity Change in China's Service Industry [J]. The Journal of Quantitative & Technical Economics, 2017,34(03).

[42] Zhengda.L, Xiaoling.Y, Yubo.S. Evaluation of the Transformation Effect of China's Economic Development Mode -- Based on EBM Luenberger Model [J]. Finance & Trade Economics, 2017,38(01).