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Assessment of Provincial Total Factor Green Energy Efficiency in China: Based on Super- SBM Model

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Abstract. Energy consumption emits large amounts of greenhouse gas, which exacerbates the problem of global warming. In order to slow down the rate of global temperature rise, improve green energy efficiency and achieve high-quality economic development, it is necessary to measure green energy efficiency accurately. By means of the Super-SBM model, this paper calculates the total factor green energy efficiency of 30 Chinese provinces from 2010 to 2017(except Tibet, Hong Kong, Macao and Taiwan), and analyzes it from the perspective of industrial structure and region. The results show that the optimization and upgrading of the secondary industry contributes to the improvement of green energy efficiency. On the whole, the green energy efficiency is declining, with remarkable regional differences: The eastern region is higher than the western region, while the western region is higher than the central region. And excessive greenhouse gas emissions in the central region are the main cause of its low green energy efficiency.

1. Introduction

Energy consumption runs through the entire process of human civilization. Before the 18th century, the energy utilized by human society was limited to some natural green energy such as hydro energy, wind energy, solar energy and biomass energy, which had not only a small quantity, but also a poor supply stability. As such, the productivity efficiency of the whole society is at a relatively backward level. After the outbreak of the industrial revolution, the fossil energy started to be used on a large scale, which brought rapid development and great progress to all areas of society. But at the same time, the excessive exploitation and use of fossil fuels also caused fearful environmental problems, like acid rain, haze, climate change and so on. In recent years, global warming has resulted in more frequent droughts, floods, extreme temperatures and other extreme weather. The contradiction between energy consumption, environmental protection and economic growth has become an urgent problem to be solved by governments and academia. As the largest country in energy consumption, China is even more so. The improvement of energy efficiency can meet both the needs of economic growth and environmental protection, which has become a momentous requirement for China's high-quality economic development. In this context, studying and analyzing the characteristics of energy efficiency will help China's economic development model towards a green, low-carbon and energy-saving recycling economy.

The concept of energy efficiency was first put forward by the world energy council in 1995. It is believed that energy efficiency refers to the energy input needed to obtain a unit of economic output, namely the energy intensity per unit of GDP. On this basis, J L Hu and S C Wang proposed the



concept of total factor energy efficiency, which is the ratio of the target input amount of energy to the actual input amount when other input factors other than energy remain unchanged[1]. With the increasingly prominent environmental problems, ecological environment, as an key influencing factor, has become part of the definition of energy efficiency. In fact, the improvement of energy efficiency should bring better economic benefits and reduce environmental pollution simultaneously[2]. So, the energy efficiency in this paper means the total factor energy efficiency taking into account the ecological and environmental factors. With respect to the estimate of energy efficiency, D Fan and W G Wang took the CO₂ generated by the consumption of coal, gasoline, kerosene, diesel, fuel oil and natural gas as the non-expected output, built an SBM model and found that the overall mean value of green energy efficiency presents a u-shaped trend and decreases in the order from east to west in the regional layout[3]. Y K Li extended the input-output index selected by D Fan and W G Wang, added the industrial structure as a new input index, and constructed the SBM-VECM model [4]. H L Yu deems that non-expected output mainly refers to the pollution discharged during production [5]. H Li and C Zhou both used the Super-SBM model. But C Zhou took the three industrial wastes as the non-expected output index [2][6]. X J Yao et al. introduced green technology as a variable, and investigated the relationship between energy efficiency and it [7]. G T Liu et al. developed and compared three models, namely, the two-year weighted modified Russell model (BWMRM) two-year bounded adjustment model (BBAM) and two-year range adjustment model (BRAM), which enhanced the accuracy of energy efficiency measurement [8]. H P Wang and M X Wang found that the overall total factor energy efficiency of cities was on the rise, and cities in different regions showed obvious gaps [9]. In addition to the domestic studies mentioned above, Y S Liu made a comparative study on total factor energy efficiency of G20 countries [10]. L Yue and Y C Yang reached the conclusion that the green energy efficiency level of 55 countries along the One Belt And One Road line was generally not high, only a few of them achieved the optimal efficiency [11].

To sum up, through the analysis of existing literature, it can be seen that few studies calculate the total factor green energy efficiency by taking greenhouse effect as the unexpected output. Therefore, this paper will build an input-output index system with greenhouse effect as the non-expected output, use the Super-SBM model to calculate the total factor green energy efficiency of 30 provinces (except Tibet, Hong Kong, Macao and Taiwan, Chongqing's data is incorporated into Sichuan) from 2010 to 2017.

2. Research methods

Data envelopment analysis (DEA) is a non-parametric method that takes the optimal output or input as the production frontier, get the data envelopment curve through linear programming, and measures the efficiency of the decision making unit. With regard to the traditional radial DEA model, The existence of relaxation variables will lead to some deviation in the efficiency evaluation results. To solve this problem, Tone constructed a new DEA model, namely SBM model. It is a non-radial and non-angle model, which can be used for efficiency evaluation based on relaxation variables to make the results more accurate. However, neither the traditional DEA model nor the SBM model could further order the efficiency level, because all the efficiency value of the effective decision-making unit is 1. So a model combining the Super-Efficiency and SBM model is generated, namely Super-SBM model, which allows the efficiency value to be greater than 1.

3. Indicator system, data source and standardization

3.1. Input indicators

3.1.1. The labor input. The ratio of the average length of schooling of the labor force in each province to that of the whole country was taken as the adjustment factor. The calculation formula is as follows, and the number of people is measured in ten thousand.

$$L_{it} = \frac{l_{it} X E_{it}}{E_t} \quad (1)$$

Where, $i = 1, 2, \dots, 29$ represents province, and $t = 2010, 2011, \dots, 2017$ stands for year. While L_{it} , I_{it} , E_{it} and E_t means the Labour force level, the actual number of workers, the average length of schooling of the labor force at provincial level and the average number of years of education for the national labor force respectively.

3.1.2. The energy input. Energy input is equal to total energy consumption, which were obtained from *China energy statistics yearbook*, and the unit is ten thousand tons of standard coal.

3.1.3. The capital input. It is relatively accurate to take capital stock as a measure of capital input. So far, there are no statistics on the capital stock, as a result, it needs to be estimated. This paper consults the method of estimating the provincial physical capital stock proposed by J Zhang et al., and uses the perpetual inventory method (taking 1952 as the base year) to estimate the physical capital stock of 30 provinces in China. Considering the price changes, the estimated capital stock data is converted into the constant prices in 2010, as shown below:

$$K_{it} = k_{it-1}(1 - \sigma_{it}) + I_{it} / P_{it} \quad (2)$$

Where, $i = 1, 2, \dots, 29$ refers to province, and $t = 2010, 2011, \dots, 2017$ represents year. While K_{it} , k_{it-1} , σ_{it} , I_{it} , and P_{it} means the capital stock of year t , the capital stock of year $t-1$, the economic depreciation rate of capital goods, the capital investment and the investment goods price index respectively. And $\sigma_{it} = 9.6\%$.

3.2. Output indicators

3.2.1. The desirable output. The GDP of each province is taken as a measure of expected output and converted to the real GDP in 2010 constant prices. The units are 100 million yuan.

3.2.2. The undesired output. In view of the unavailability of some data, three major greenhouse gases generated by six major energy sources as unexpected outputs are chosen as undesired output. The six main types of energy are coal, gasoline, kerosene, diesel fuel oil and natural gas, and the greenhouse gases are carbon dioxide, methane and nitrous oxide. Among them, the carbon emissions from energy consumption can be calculated with the 2006 IPCC guidelines for national greenhouse gas inventories.

$$CO_2 = \sum_{i=1}^6 CO_{2i} = \sum_{i=1}^6 E_i \times NCV_i \times CEF_i \times COF \times 44 / 12 \quad (3)$$

Where, $i = 1, 2, \dots, 6$ stands for province, and E_i , NCV_i , CEF_i , and COF refers to the consumption of energy, the net calorific value of energy, the carbon emission coefficient of energy and carbon oxidation factor respectively.

Besides, methane and nitrous oxide emissions can be calculated in the light of the default emission factors from energy burning, which is taken from the 2006 IPCC guidelines for national greenhouse gas inventories, and the calorific value of energy. After the greenhouse gas emissions of each province from 2010 to 2017 were calculated. The global warming potential value (GWP) was used to represent the greenhouse effect generated by energy consumption.

3.3. Raw data and its standardization

When the input-output data was obtained, the next step is to standardized it. The standardized method adopted by J.Lan et. al. in the study *Evaluation of low carbon economy efficiency in Hubei province based on cross DEA model* is learned. Take the data in 2017 as an example, since GWP is a reverse indicator, forward processing is required. Other indicators can be standardized, and the processed data are shown in table 1.

Table 1. Standardized data of green energy efficiency evaluation of Chinese provinces in 2017

DMU	(I)EC	(I)LF	(I)GFCF	(O)GDP	(O)GWP
Beijing	0.2238	0.2910	0.3350	0.3624	0.9439

Tianjin	0.2454	0.2042	0.3556	0.2646	0.9249
Hebei	0.7958	0.6549	0.5875	0.4244	0.4806
Shanxi	0.5417	0.3385	0.2743	0.2334	0.2200
Neimenggu	0.5382	0.2596	0.4091	0.2392	0.3064
Liaoning	0.5786	0.3900	0.4682	0.3148	0.6438
Jinlin	0.2455	0.2672	0.3607	0.2273	0.8495
Heilongjiang	0.3567	0.3383	0.3090	0.2372	0.7450
Shanghai	0.3400	0.2986	0.3629	0.3895	0.8609
Jiangsu	0.8215	0.7678	0.9398	0.9604	0.4205
Zhejiang	0.5657	0.6230	0.6303	0.6079	0.6878
Anhui	0.3694	0.6026	0.3576	0.3521	0.7038
Fujian	0.3654	0.4480	0.4794	0.4055	0.8558
Jingxi	0.2696	0.4079	0.2629	0.2796	0.8709
Shandong	1.0000	0.9656	1.0000	0.8236	0.1000
Henan	0.6127	0.9761	0.8117	0.5333	0.5519
Hubei	0.4702	0.5556	0.4853	0.4395	0.7624
Hunan	0.4461	0.5969	0.4263	0.4233	0.7706
Guangdong	0.8440	1.0000	0.9686	1.0000	0.5637
Guangxi	0.3056	0.4399	0.3648	0.2643	0.8913
Hainan	0.1000	0.1384	0.1000	0.1190	1.0000
Sichuan	0.7967	0.9077	0.6865	0.6558	0.6135
Guizhou	0.3061	0.2888	0.2203	0.2128	0.7705
Yunnan	0.3211	0.4124	0.3484	0.2421	0.8804
Shanxi	0.3567	0.3548	0.3513	0.2992	0.6271
Gansu	0.2337	0.2565	0.1504	0.1500	0.9052
Qianghai	0.1516	0.1000	0.1105	0.1000	0.9904
Ningxia	0.2079	0.1095	0.1187	0.1085	0.8303
Xinjiang	0.4762	0.2479	0.2525	0.1853	0.6063

4. Empirical results and analysis

The green energy efficiency of 30 Chinese provinces from 2010 to 2017 is shown in table 2.

Table 2. Green energy efficiency of Chinese provinces from 2010 to 2017

DMU	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.0992	1.1221	1.1238	1.1466	1.1469	1.1554	1.1615	1.1655
Tianjin	0.9354	0.9401	1.0022	1.0062	1.0378	1.0260	1.0208	1.0166
Hebei	0.4169	0.3920	0.3940	0.3438	0.3766	0.3691	0.3777	0.3639
Shanxi	0.3592	0.3296	0.3270	0.2384	0.2442	0.2640	0.2869	0.2064
Neimenggu	0.4542	0.3470	0.3391	0.3089	0.3063	0.3275	0.3292	0.2638
Liaoning	0.5977	0.6081	0.6168	0.5920	0.5858	0.5804	0.4445	0.4381
Jinlin	0.6462	0.6484	0.6638	0.6497	0.6480	0.6370	0.6292	0.6118
Heilongjiang	0.6183	0.6328	0.6178	0.5913	0.5756	0.5466	0.5268	0.5118
Shanghai	1.0827	1.0779	1.0635	1.0569	1.0023	1.0045	1.0135	1.0155
Jiangsu	1.0343	1.0494	1.0527	1.0685	1.0813	1.0742	1.0759	1.0810
Zhejiang	0.8560	0.8609	0.8668	0.8401	0.8410	0.8298	0.8275	0.8155
Anhui	0.6347	0.6516	0.6443	0.5819	0.5782	0.5667	0.5646	0.5610
Fujian	0.7770	0.7454	0.7526	0.7349	0.7271	0.7250	0.7276	0.7272
Jingxi	0.7555	0.7846	0.7922	0.7817	1.0015	1.0005	0.7146	0.7061
Shandong	0.2137	0.2129	0.2114	0.2230	0.2169	0.2063	0.1991	0.1993
Henan	0.4418	0.4151	0.4599	0.4287	0.4465	0.4486	0.4561	0.4623
Hubei	0.6185	0.6093	0.6257	0.6577	0.6693	0.6731	0.6714	0.6592
Hunan	0.6778	0.6755	0.6979	0.6803	0.6923	0.6907	0.6789	0.6609

Guangdong	1.1013	1.1109	1.1201	1.1268	1.1157	1.1251	1.1279	1.1131
Guangxi	0.6388	0.6229	0.6172	0.6007	0.5994	0.5926	0.5810	0.5596
Hainan	1.1631	1.1850	1.2045	1.2444	1.2552	1.2596	1.2707	1.2870
Sichuan	0.5215	0.5521	0.5836	0.5908	0.6071	0.6318	0.6451	0.6603
Guizhou	0.5800	0.5803	0.5873	0.5806	0.5982	0.6091	0.5942	0.5963
Yunnan	0.5683	0.5629	0.5622	0.5513	0.5482	0.5449	0.5295	0.5252
Shanxi	0.6309	0.6225	0.6119	0.5730	0.5637	0.5509	0.5328	0.5341
Gansu	0.6814	0.6758	0.6819	0.6668	0.6661	0.6420	0.6323	0.6278
Qianghai	1.1113	1.1015	1.1098	1.1128	1.1174	1.1145	1.1024	1.1226
Ningxia	0.8593	0.8658	0.8850	0.8842	0.8860	0.8492	0.8490	0.8097
Xinjiang	0.6659	0.6506	0.6171	0.5457	0.5159	0.4712	0.4416	0.4209

4.1. Analysis based on industrial structure

Apart from several provinces like Beijing and Hainan, most regions in China take industry as the leading industry. On the grounds of the estimation of relevant experts, if the output of industry and services is the same, the former consumes far more energy and produces about five times as much pollution as the latter. In theory, there exists a certain relationship between industrial proportion and energy efficiency. Figure 1 shows the mean value of industrial proportion and green energy efficiency in the 30 provinces over the period from 2010 to 2017. It is observed that they have a roughly opposite trend, that is, when industrial proportion declines, energy efficiency will increase; otherwise, energy efficiency will decrease.

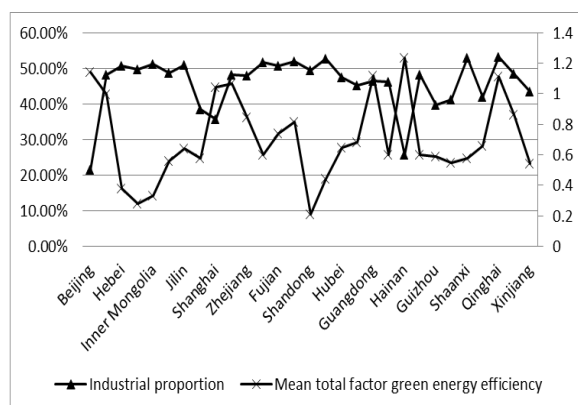


Figure 1. Average industrial proportion and green energy efficiency of each province from 2010 to 2017.

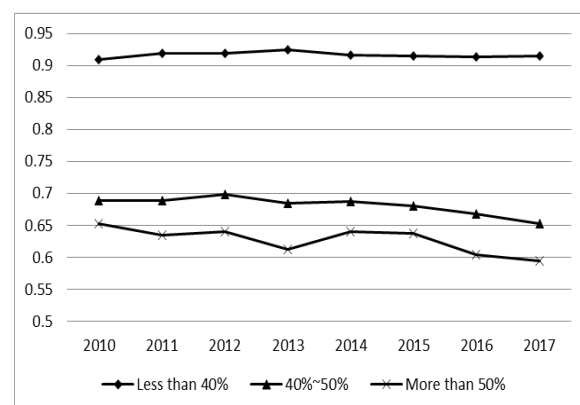


Figure 2. The performance of regions with different industrial proportions in green energy efficiency.

According to the industrial proportion, this paper divides the study objects into three groups, which are the regions with industrial proportion less than 40%, 40%~50% and more than 50%. As shown in figure 2, the mean green energy efficiency of those regions where the industrial proportion is less than 40%, is basically stable at above 0.9. Nevertheless, the other two groups are at a low level and show a downward trend from 2010 to 2017. The average green energy efficiency of regions with 40%~50% industrial proportion is slightly higher than that of regions with more than 50% industrial proportion, with 0.65~0.7 for the former and 0.6~0.65 for the latter.

4.2. Analysis of regional green energy efficiency in China

In figure 3, it's obvious that the green energy efficiency of the three regions in China are declining on the whole from 2010 to 2017. About the magnitude of the descend, the eastern region is the smallest, and the western region is slightly higher than the central region. Especially in 2015, the green energy efficiency of the three regions showed a comparatively large rate of decent.

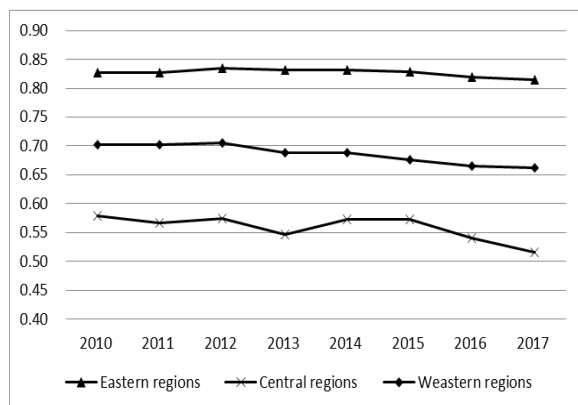


Figure 3. Average green energy efficiency of China's three regions.

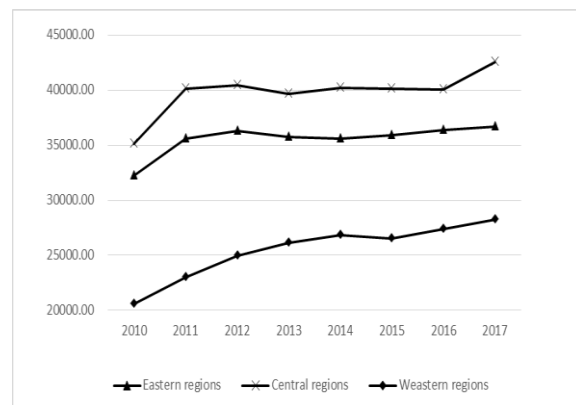


Figure 4. The average GWP of the three regions in China.

The eastern region has the highest mean green energy efficiency ranging from 0.8 to 0.85, followed by the western region between 0.65 and 0.7 and the lowest in the central region between 0.5 and 0.6. This conclusion differs from that of the past, which may be caused by GWP. As can be seen from figure 4, GWP continued to rise in all three regions from 2010 to 2017, with the highest GWP in the central region. Compared with the western region, excessive GWP in the central region tremendously reduces its green energy efficiency and results in a change in the ranking of the two.

5. Conclusions

Above all, this paper calculated the green energy efficiency of 30 Chinese provinces (except Tibet, Hong Kong, Macao and Taiwan) firstly, and then divided the research objects into three groups of regions according to the industrial proportion. After that, the characteristics of the three group's green energy efficiency were analyzed. Finally this article analyzed the differences in green energy efficiency among the three regions of China, and made explanations in accordance with data. The conclusions are as follows: (1) there is an opposite trend between the industrial proportion and green energy efficiency, that is, the optimization and upgrading of industrial structure will effectively promote the improvement of green energy efficiency. (2) Regional differences exist in China's green energy efficiency. And the eastern region is higher than the western region, while the western region is higher than the central region. (3) the lowest green energy efficiency in the central region is a result of its excessive greenhouse gas emissions.

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