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Research on China's Carbon Emission Efficiency and Its Regional Differences

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Abstract: With the development of China's economy, China is emitting more and more carbon. At the same time, it has also exposed the problem of carbon emission efficiency differences caused by the unbalanced development of resources and economy among regions. Based on the carbon emission panel data of provinces and cities in China from 2009 to 2018, this paper studies carbon emission efficiency and regional differences by constructing a three-stage data envelopment analysis (DEA) model that eliminates the influence of environmental factors and random factors. The research shows that: (1) Carbon emission efficiency in China is spatially distributed; carbon emission efficiency in the western region is generally lower than that in the eastern region. (2) China's carbon emission efficiency is not entirely synchronized with economic development; carbon emission efficiency in some underdeveloped western regions has reached the forefront of China, and some developed regions in the east are in the middle position. (3) China's carbon emission efficiency is restricted by scale efficiency; many regions in China have high pure technical efficiency, but due to low scale efficiency, overall efficiency is low. (4) Overall, China's carbon emission efficiency is currently on the rise, but the rising rate is relatively slow, and there is still plenty of room for improvement.

Keywords: three-stage DEA model; SFA; carbon emission efficiency; regional differences

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1. Introduction

In recent years, with the melting of Arctic glaciers, rising sea, and global warming, climate-related environmental problems have become increasingly severe, and the primary factor that leads to such drastic climate change is the increase of carbon dioxide emissions. The international community has already begun to pay attention to carbon dioxide emissions. The Paris deal was born in 2016, and a total of 196 countries signed the agreement, which promised global temperature would rise below 2 °C by the end of the century by reducing the emission of carbon dioxide [1]. How to reduce carbon emissions and improve carbon efficiency has become a problem that human society needs to face. Since 2006, China has become the world's largest carbon dioxide country; emission of carbon dioxide has become a severe threat to human health and nature [2,3]. In response to the concerns of carbon dioxide emission, on 7 October 2021, the Chinese government issued an opinion on the pollution control battle, proposing that by 2025, carbon dioxide emissions per unit of GDP (gross domestic product) should be reduced by 18%, compared to 2020.

Based on the above background, "low-carbon" and "emission reduction" have become hot topics in academic research. An increasing number of scholars have begun to estimate the amount of carbon dioxide emissions [4,5], its influencing factors [6–8], strength [9,10], and efficiency [11]. As an essential part of environmental performance evaluation, carbon emission efficiency is the focus of many scholars who study the environment, and it can effectively measure carbon dioxide emissions per unit of GDP [12]. A large number of studies have shown that economic development can lead to an increase in carbon dioxide emissions [13–15]. Therefore, governments and academia are committed to exploring the influencing factors of carbon emission efficiency to find measures that can reduce carbon dioxide emissions, and improve carbon emission efficiency. Currently, the research on carbon emission efficiency can be divided into two categories. The first category is single-element indicators. Mielnik and Goldemberg first used carbon emissions per unit of energy consumption to evaluate the carbon emission performance of developing countries [16]. Yamaji et al. defined the ratio of total CO_2 emissions to GDP as carbon dioxide production, in order to study the level of carbon emissions in Japan [17]. Since then, other single-factor indicators have gradually emerged, including fossil energy consumption [18], CO_2 emissions per capita [19], energy structure [20], and energy intensity [21]. The second category is the total factor. Zhang et al. studied the change and decomposition of dynamic CO_2 emission performance in China from 2002 to 2010, and found the total factor carbon performance of the transportation industry decreased by 32.8%, due to technological decline [22]. Chen and Golley used CO_2 emissions as unexpected output directly into production technology to estimate the change in the "green" total factor productivity (GTFP) growth pattern of 38 industrial sectors, from 1980–2010 [23]. In addition, a large number of scholars have studied carbon dioxide emission rates from spatial scales, such as Nassar R et al., who discussed the temporal and spatial distribution of carbon emission efficiency by collecting carbon dioxide emission data of fossil fuels in various countries around the world; thus setting off a wave of research on the characteristics of carbon emission efficiency on the space scale in the academic community [24]. Uddin and Smirnov analyzed the geographical and spatial distribution of carbon dioxide emissions by observing satellite data, and studied the impact and structural nature of regional, specific sector emissions in the total carbon budget [25]. Yu Z calculated the carbon emissions generated by energy consumption in China's provinces, further calculated carbon emission efficiency, and also studied the spatial distribution pattern of China's carbon emission efficiency [26]. Different from others' research on the overall distribution of carbon emissions in China, Chen X et al. refined their research scope to carbon dioxide produced by the transportation industry, and investigated the spatial change of carbon dioxide emissions in East China [27]. Wang B and Liu F et al. analyzed the driving factors of carbon dioxide emissions in the allocation of industrial resources in various provinces of China, from the spatial perspective, and found that improving the distribution of industrial resources can reduce carbon dioxide emissions [28,29]. In terms of research methods, in order to strengthen the detailed research on the single factor and total factor of carbon emission efficiency, scholars began to widely use DEA as a research tool [30]. Iram et al. used DEA to explore the role of energy efficiency in carbon dioxide emissions, and the results showed that there is a strong link between energy efficiency and carbon emissions [31]. Wang et al. used DEA to estimate carbon emission efficiency and emission reduction potential of Chinese provinces, from 2003 to 2016. The research results showed that there is a negative correlation between resource richness and carbon emission efficiency; the richer the resources, the lower the emission efficiency [32]. Ke et al. used the DEA method to assess regional energy and emission efficiency in 30 major cities in China, from 2006 to 2010, and found the highest in coastal cities [33]. Zhang and Choi studied the dynamic changes in CO_2 emission performance of fossil fuel power plants, from 2005 to 2010, and the results showed that CO_2 emissions improved by 0.38% over the sample period [34].

It can be seen that some scholars have explored single factors related to economic development, energy consumption, and urban population size [35]. Some scholars have combined them to examine the performance of whole factor carbon emissions, while adding spatial elements and DEA methods to explore carbon dioxide, which makes research on carbon emissions more and more diverse. Although many scholars have explored the influencing factors of carbon emission efficiency from different angles, there are few studies on the regional impact of carbon emission efficiency, and most of these use the traditional DEA method for research, which is prone to be disturbed by random factors. Therefore, first, this paper adopts the three-stage DEA method excluding other factors, and studies carbon emission efficiency from the perspective of total factors. Second, according to the traditional regional classification, China is divided into eastern, central, and western regions, in order to more accurately examine the differences in carbon emission efficiency among China's inter-provincial regions. Finally, relevant policy recommendations are put forward based on the research conclusions, so as to provide support for China to achieve carbon peak faster.

2. Methodology

2.1. Introduction to the Research Methods

2.1.1. The First Stage of DEA

DEA was first proposed by Chames et al., then revised by Banker et al. and offered a more rigorous model, which decomposes technical efficiency into pure technical efficiency and scale efficiency, to solve the effectiveness of scale compensation under variable conditions [36,37]. The traditional DEA model (namely the BCC model) can be used to obtain the input difference value or output difference value. Referring to research on carbon emission efficiency by domestic and foreign scholars, the input-oriented BCC model is constructed as follows:

$$\begin{aligned} &\min_{\theta\lambda} = \left[\theta - \left(e^t s^- + e^t s_+\right)\right] \\ &\sum_{k=1}^{n} \lambda_i y_{rk} - s^+ = y_{ok} \\ &\sum_{k=1}^{n} \lambda_i y_{rk} + s^- = \theta x_{ok} \\ &\sum_{k=1}^{n} \lambda_k = 1 \\ &\lambda_k \geq 0; s^+ \geq 0; s^- \geq 0 \end{aligned} \tag{1}$$

In Formula (1), i = 1, 2, ..., x; k = 1, 2, ..., n; r = 1, 2, ..., y. While n is the number of decision units, x and y are the number of input and output variables, respectively, y_{ik} (i = 1, 2, ..., x) is the i-th input element of the k-th decision unit, y_{rk} (r = 1, 2, ..., y) is the r-th output element of the k-th decision unit, θ is the effective value of the decision unit. If $\theta = 1$, and $s^+ = s^- = 0$, the decision unit DEA is valid; if $\theta = 1$, and $s^+ \neq 0$ or $s^- \neq 0$, it is weak DEA. And if $\theta < 1$, the decision unit is not a DEA and is valid.

2.1.2. The Second Stage of DEA

Carbon emission efficiency is disturbed by internal factors, external factors, and random factors. The random factors refer to an error phenomenon that may occur randomly in the process of formula calculation, and in the process of data collection. It includes: statistical errors of data; omitted variables in regression models; some subjective and spontaneous behaviors of people in calculation; imperfect forms of established mathematical model; combined errors between economic variables; and combined errors in measurement, etc. [38]. Therefore, the stochastic frontier analysis (SFA) model is constructed to decompose the relaxation variable into a function containing three independent variables: environmental factors; random factors; and management factors, to remove these influencing factors and readjust the data for easy calculation [39,40]. Its expression is as follows:

$$S_{ni} = f^n(Z_i; \beta^n) + V_{ni} + U_{ni} \tag{2}$$

In Formula (2), $n = 1, 2, \ldots, N$, N represents n inputs; $i = 1, 2, \ldots, I$, I represents i decision units. S_{ni} is the relaxation variable of the i-th decision unit on the n-th input. The difference between the ideal input and the actual input; $f^n(Z_i;\beta^n)$ is used to represent the influence of environmental factors on S_{ni}. Usually, take $f^n(Z_i;\beta^n) = Zi\beta n$, the Z_i is the environmental variable of the observed k-dimension, the βn is the parameter vector corresponding to the environment variable; $V_{ni} + U_{ni}$ is known as the common error term ε_i; The V_{ni} reflects the random error, which is normally distributed, namely, $U_{ni} \in N(0, \sigma^2{}_{vn})$. The U_{ni} reflects the inefficiency of the management, with a truncated normal distribution, namely, $Uni \in N(\mu_u, \sigma^2{}_{un})$, generally speaking $\mu_u = 0$, $U_{ni} > 0$. The V_{ni} and U_{ni} are not associated with the independent. Estimates of the β^n, and equal parameters are then calculated by maximum likelihood estimation. Then V_{ni} is calculated $_i$ according to the above parameters.

$$X^*_{ni} = X_{ni} + [\max(Z_i\beta^n) - Z_i\beta^n] + [\max(V_{ni} - V_{ni})] \\ n = 1, 2, \ldots, N; i = n = 1, 2, \ldots, I \tag{3}$$

In Formula (3), $X^*{}_{ni}$ is the new input value of the original input X_{ni} adjusted after homogenization, the first middle bracket adjusts the influence of environmental factors, $\max(Z_i\beta_n)$ represents the is in the worst, environmental condition, and other decision units are adjusted on their basis. If the effect is good, increase more input; if the effect is poor, increase less input, so that all decision units are adjusted to the same environmental level. The adjustment in the second middle bracket is the random error factor, on the same principle, giving all decision units the same conditions.

2.1.3. The Third Stage of DEA

The DEA in the third stage and the DEA model used in the first stage adopt the input-oriented DEA-BCC model. The difference is that the relative efficiency of each decision unit is calculated similarly by substituting the environmental factors and random factors X^*_{ni} into the DEA-BCC model in the first stage, to obtain a more accurate value.

2.2. Data Description

2.2.1. Introduction of Related Variables

The input variables selected in this paper are the size of population, capital stock, and energy consumption, which are associated with economic variables. Hao C et al. proved that the rapid growth of the total population can promote the increase of carbon emissions, through research on the carbon emissions of the BRICS countries; the growth of the population and the economic benefits can affect the carbon emissions efficiency to a certain extent [41]. Therefore, this paper selects the size of population as a secondary variable in the selection of input indicators, and uses the total population at the end of the year to represent the size of population [41]. The capital stock is expressed by the industrial energy investment of each region. The use of industrial energy investment can most directly reflect the economic input of carbon emissions of each region [42]. Xu et al. proposed that energy consumption and industrial production emissions should be given priority by studying the composition of carbon emissions [43], so the total energy consumption of each region is selected as the energy consumption. Among the output variables, GDP and carbon emissions are chosen, among which GDP, as an output variable, occupies the mainstream position in current academic research on carbon emission efficiency. For example, Zhu J believed that carbon emission efficiency is related to carbon emission and economy, and GDP, as the best variable to measure the economy, should be regarded as an output variable; therefore, this paper takes it as expected outputs [44]. Zhang W et al. believed that carbon emissions are the accompaniment of economic development, with the development of the economy, the rise of industry and energy industry inevitably bringing a large amount of carbon emissions [45]. Therefore, this paper uses carbon emissions as an output variable, accordingly.

The calculation of carbon emissions is based on the United Nations Intergovernmental Special Committee on Climate (IPCC) carbon emission coefficient, and collects the provinces and cities of coal, coke, crude oil, natural gas, and another eight kinds of energy consumption. Due to the carbon emission coefficient of resources such as water, wind and light energy being 0, which does not produce carbon emissions, they are excluded from the calculation. This paper uses the carbon emission coefficient method to calculate carbon emission, and the estimation formula is as follows:

$$Q_{co_2} = E \times K \tag{4}$$

In Formula (4), E represents energy sources in different types, and its unit is standard coal/ton. K is the carbon emission factor of various energy sources, as revised in 2019. In addition, this paper takes the level of economic development, national consumption, and scientific and technological progress as environmental variables. The changes in these environmental variables affect the efficiency of carbon emissions to a certain extent. The level of economic development is expressed by per capita GDP. If people's living standards improve, they will have more money to consume items that release carbon dioxide, such as cars, air-conditioning, etc. In other words, the increase in per capital GDP will increase carbon dioxide emissions; carbon emission efficiency is an output indicator, which is composed of the ratio of unit GDP to carbon dioxide emissions. National consumption uses the total amount of social consumer goods in various regions, which most intuitively shows the consumption capacity. In the process of consumption, people will inevitably consume energy consuming goods. The increase in per capital household consumption can indirectly lead to a rise in carbon emissions [46]. Therefore, if people's total social consumption is more significant, carbon emissions in this region will increase accordingly; the increase of carbon emissions will increase the local environmental pressure, and then reduce the efficiency of carbon emissions. Technological innovation can effectively reduce the intensity of carbon dioxide emissions from the source by improving the efficiency of energy utilization, to enhance the efficiency of carbon emissions [47]. Therefore, this paper selects the number of valid patents in each region this year, as an indicator of scientific and technological progress. Based on this, the scientific index system is constructed (see Table 1).

Table 1. Index system of carbon emission efficiency.

Level 1 Indicators	Secondary Indicators	Level 3 Indicators
Input indexes	Size of population Stock of capital Energy use	Total population at the end of the year (/10,000) Industrial energy investment (/RMB 100 million) Total regional energy consumption (/Million tons)
Output indexes	Carbon emission GDP	Carbon emissions from each region (/Ton) Total GDP (/100 million yuan)
External environment variables	Economic development National consumption Scientific and technological	Per capita GDP (/Ten thousand yuan) Total social consumer goods (/100 million yuan) Patent valid (/Piece)

2.2.2. Data Source

The data in this paper are from *China Statistical Yearbook*, *China Energy Statistical Yearbook* [48], *China Environmental Statistical Yearbook* [49] and *China Science and Technology Statistical Yearbook* [50]. The period is from 2009 to 2018. In this period, China has just passed the financial crisis, which was in a period of rapid economic development. Due to the lack of data in Hong Kong, Macao, Taiwan, and the Tibet region, we selected 30 provinces and cities outside of those four regions. For convenient comparison, this paper divides the 30 province and cities into eastern, central, and western regions.

3. Results

3.1. The First Stage of the Traditional DEA Analysis

In the first stage, original data on the input and output of carbon emissions from 30 provinces and cities were collected, and MaxDEA 5.2 (It was created by Mr. Cheng Gang of China.) was used to build a DEA-BCC model for calculation. The average efficiency of carbon emissions, from 2009 to 2018, is shown in Table 2. The 30 provinces and cities were divided into eastern region, central region and western region, and their carbon emission efficiency are shown in Figure 1.

Table 2. Average carbon emission efficiency from 2009 to 2018.

Area	Carbon Emission Efficiency	Pure Technical Efficiency	Scale Efficiency	Area	Carbon Emission Efficiency	Pure Technical Efficiency	Scale Efficiency
Beijing	1.000	1.000	1.000	Henan	0.775	0.813	0.923
Tianjin	0.992	0.998	0.990	Hubei	0.761	0.765	0.953
Hebei	0.839	0.858	0.975	Hunan	0.693	0.708	0.934
Shanxi	0.985	0.998	0.987	Guangdong	0.857	1.000	0.846
Nei Monggol	1.000	1.000	1.000	Guangxi	0.715	0.720	0.946
Liaoning	0.992	1.000	1.000	Hainan	0.975	1.000	0.983
Jilin	0.877	0.878	0.980	Chongqing	0.696	0.675	0.974
Heilongjiang	0.821	0.834	0.964	Sichuan	0.616	0.619	0.928
Shanghai	0.992	1.000	1.000	Guizhou	0.738	0.756	0.947
Jiangsu	0.986	1.000	0.988	Yunnan	0.608	0.609	0.944
Zhejiang	0.891	0.916	0.969	Shaanxi	0.961	0.967	0.986
Anhui	0.834	0.905	0.912	Gansu	0.714	0.712	0.971
Fujian	0.865	0.869	0.972	Qinghai	0.524	1.000	0.477
Jiangxi	0.819	0.838	0.955	Ningxia	0.999	1.000	0.997
Shandong	0.965	1.000	0.973	Xinjiang	0.807	0.821	0.991
Average	Carbon emission efficiency: 0.843		Pure technical efficiency: 0.875		Scale efficiency: 0.949		

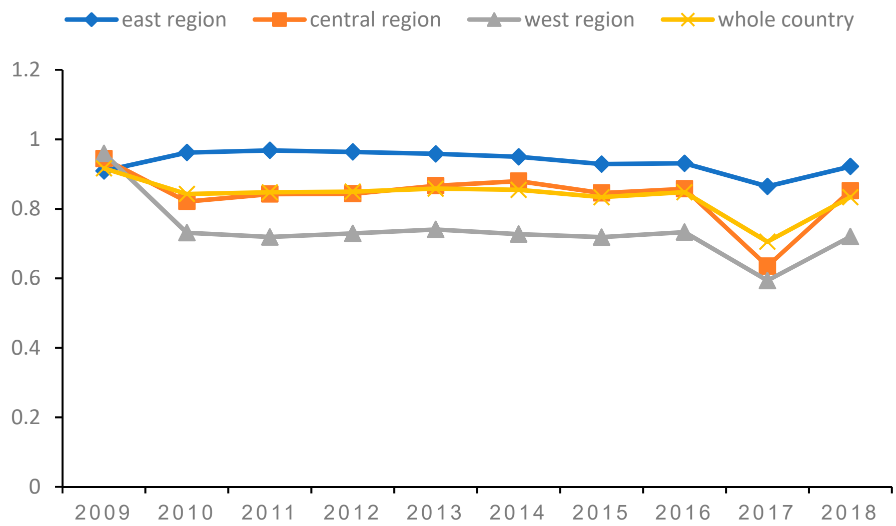

Figure 1. The change of carbon emission efficiency, from 2009 to 2018, in the first stage.

From the results of Table 2, without considering the influence of external environmental factors and other random factors, the overall carbon emission efficiency of China over the years has been relatively stable; but the carbon emission efficiency gap is noticeable, and needs controlling in the future. The results show that from 2009 to 2018, the average carbon emission efficiency of 30 provinces and cities was 0.843, the average pure technical efficiency was 0.875, and the average value of scale efficiency was 0.949. The average annual carbon emission efficiency is 16 percentage points different from that of the highest, among the 30 provinces and cities; the average yearly pure technical efficiency is 13 percentage points further; and the scale efficiency is increased by 6 percentage points. There is much room for improvement in these regions. By comprehensively analyzing the carbon emission efficiency of the two stages, this paper divided 30 provinces and cities into three regions: high, medium, and low, according to their efficiency. At the same time, in this study, the carbon emission efficiency is in the field of 0–1. Therefore, 0.6 and 0.9 are taken as the dividing points: the carbon emission efficiency of 0~0.6 is the low-efficiency area; the carbon emission efficiency of 0.6 to 0.9 is the medium efficiency area; and the carbon emission efficiency of 0.9~1 is the high-efficiency area. It can be seen from Table 2, that the 11 provinces with high carbon emission efficiency levels are: Beijing, Tianjin, Shanxi, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Shandong, Hainan, Shaanxi, and Ningxia. There are 18 provinces with medium efficiency, including: Hebei, Jilin, Heilongjiang, Zhejiang, Anhui, Fujian, Jiangxi, Hunan, Hubei, Henan, Guangdong, Guangxi, Chongqing, Sichuan, Yunnan, Guizhou, Gansu, and Xinjiang. Only Qinghai province is in the low-efficiency area. The results show that carbon emission efficiency is not entirely synchronized with economic development; carbon emission efficiency of backward provinces is not necessarily low, and carbon emission efficiency of developed provinces is not necessarily high. It can be seen that although carbon emission efficiency is primarily linked to the economy, it is not entirely dependent on the economy. It is affected by other factors, such as population [51], terrain [52], policies [53], and scientific and technological levels [54], which can impact carbon emission efficiency to some extent.

As shown in Figure 1, there are significant differences in carbon emission efficiency among the eastern region, central region, and western region, from 2009 to 2018. The average carbon emission efficiencies in the eastern region, central region, and western region are 0.941, 0.841, and 0.738, respectively. The reason lies in the relatively developed economy and mature concept of environmental protection in eastern coastal areas. The local governments attach more importance to environmental protection, and invest more in it [55]. Since the reform and opening up in Western China, energy-consuming industries have dominated the region. In addition, in recent years, many factories in central and eastern regions have been relocated to the western region, resulting in increased environmental pressure and low carbon emission efficiency. In addition, it can be seen from Figure 1, that from 2010 to 2016 the average carbon efficiency was relatively stable and slow to change. In addition to the central region, eastern and western regions were vaguely declining. Until 2017, national carbon efficiency improved rapidly. This may be due to the Chinese release of a series of policies, such as the 13th Five-Year Plan for National Environmental Protection Standards, and the Regulations on the Implementation of the Environmental Protection Tax Law, which helped to improve the efficiency of fossil energy utilization, increased the production of renewable energy, and increased investment in environmental pollution protection. It is worth noting that carbon emission efficiency of the central region was consistent with the whole country. Therefore, it can be considered that, to some extent, the internal management level of carbon emission efficiency in the central region is roughly equivalent to the internal management level of national carbon emissions.

In addition, because of resource endowments and different economic development, carbon emission efficiency among different provinces and cities are also inevitably disturbed by the environment, and other random factors [56]. The areas with better geographical location and economic conditions have higher carbon emission efficiency. In contrast, areas with poor geographical environment, weak economic development and foreign investment, have lower carbon emission efficiency. The results of Table 2, therefore, cannot truly reflect the level of carbon emission efficiency in China. It is necessary to make adjustments and calculations to obtain more accurate and reliable results.

3.2. The Second Stage of the SFA Analysis

Taking the labor force, capital stock, and energy consumption of 30 provinces and cities in China from 2009 to 2018 as dependent variables, and external environmental variables, we established the SFA regression analysis model. Through R language software, the relaxation variable values of the three input variables in the first stage were regressed and analyzed, by using the maximum likelihood method. The results are in Table 3.

It can be seen from Table 3 that, in addition to per capita GDP, the total retail sales of consumer goods, and the number of valid patents, are significantly related to the population, energy consumption, and the slack in energy-industry investment, which shows that the level of per capita GDP has no effect on the improvement of carbon emission efficiency. However, the one-sided error tests, for final LR (likelihood) all passed the 1% test, so all environmental variables should be considered when correcting for input outputs. According to the analysis of Table 3, it can be seen that the economic development level, national consumption, and scientific and technological progress selected in this paper have positive or negative effects on input variables. Therefore, this paper adjusted the input variables such as labor force, capital stock, and energy consumption in 30 provinces and cities in China from 2009 to 2018, to removing the environmental factors and random factors that affect the results. The adjusted variable results are in Table 4.

Table 3. Results of the regression analysis of the 30 provinces and cities from 2009 to 2018.

Population	Coefficient	Standard Error	T-Ratio	p-Value
Cow distance item	−944	158	−6	0
per capita GDP	4	20	0	1
Total retail sales of consumer goods	0	0	5	0
Number of valid patents	0	0	−3	0
sigmasq	34,900,000	1	3,490,000	0
gamma	1	0	524	0
Log- likelihood function	−2190			
LR test of the one-sided error	716			
One-sided likelihood ratio test for p-values	0			
Energy Consumption	**Coefficient**	**Standard Error**	**T-Ratio**	**p-Value**
Cow distance item	−17,000	417	−4	0
per capita GDP	92	56	2	0
Total retail sales of consumer goods	0	0	4	0
Number of valid patents	0	0	−2	0
Sigmasq	79,600,000	1	7,960,000	0
Gamma	1	0	58	0
Log -likelihood function	−26,000			
LR test of the one-sided error	229			
One-sided likelihood ratio test for p-values	0.000			
Energy Industry Investment	**Coefficient**	**Standard Error**	**T-Ratio**	**p-Value**
Cow distance item	−177	50	−4	0
per capita GDP	11	7	2	0
Total retail sales of consumer goods	0	0	3	0
Number of valid patents	0	0	−2	0
Sigmasq	868,000	1	841,000	0
Gamma	1	0	31	0
Log- likelihood function	−1974			
LR test of the one-sided error	143			
One-sided likelihood ratio test for p-values	0			

Table 4. Data adjusted for raw data by SFA method (take 2018 as an example).

Area	Population	Energy Consumption	Investment Amount in Industrial Energy Sources	Area	Population	Energy Consumption	Investment Amount in Industrial Energy Sources
Beijing	3480	11,600	1184	Henan	10,100	25,000	2320
Tianjin	2870	12,000	1220	Hubei	6600	19,200	1520
Hebei	8300	33,900	2550	Hunan	7660	18,300	1444
Shanxi	4890	24,600	1950	Guangdong	12,200	37,600	2320
NeiMonggol	3680	27,300	2770	Guangxi	5990	14,300	1400
Liaoning	5310	26,500	1510	Hainan	2330	6710	886
Jilin	3820	11,100	1280	Chongqing	4260	12,000	1090
Heilongjiang	4810	14,800	1360	Sichuan	9030	22,100	19,601
Shanghai	3570	15,600	907	Guizhou	4890	13,700	1230
Jiangsu	8850	35,600	2310	Yunnan	5960	14,800	1320
Zhejiang	6680	24,700	1700	Shaanxi	4980	17,100	2190
Anhui	7340	17,200	1670	Gansu	3950	11,700	1080
Fujian	4910	16,400	1520	Qinghai	2040	890	1190
Jiangxi	5792	13,100	1290	Ningxia	2120	11,700	1330
Shandong	10,700	44,400	4100	Xinjiang	3820	21,200	1970

3.3. Empirical Results of DEA after Adjustment in the Third Stage

In this paper, input variables such as population, energy consumption, and industrial energy investment, which are affected by environmental factors and random factors, were removed and reintroduced into the traditional DEA-BCC model, used in the first stage. MaxDEA software was used to calculate the carbon emission efficiency of 30 provinces and cities in China from 2009 to 2018. Compared with the efficiency value of the original data directly in the first stage, the carbon emission efficiency value obtained in the third stage has been eliminated from environmental factors, and other random factors. It more truly reflects the real carbon emission efficiency of all provinces and cities in China. The following are the changes in efficiency values in the third stage (see Figure 2), and the comparison of average efficiency values in the first and third stages (see Table 5).

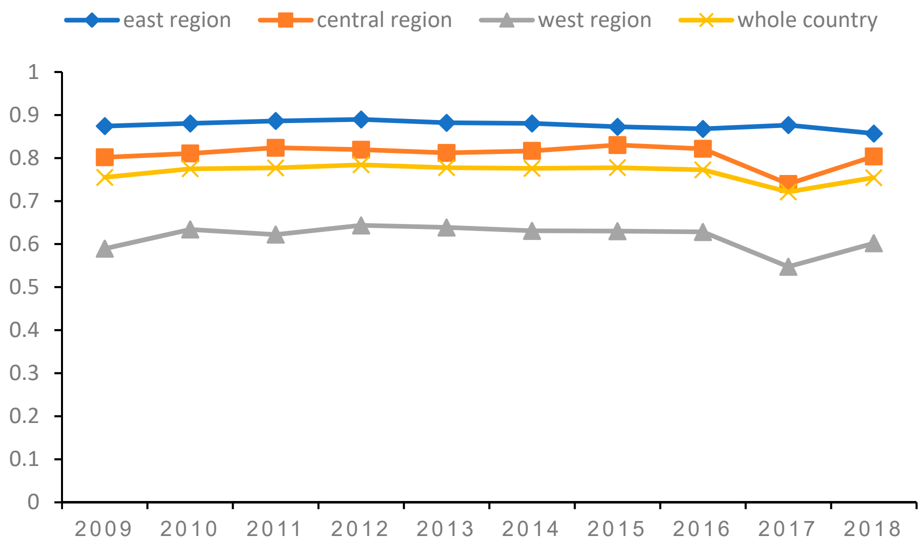

Figure 2. The third stage is the mean change of carbon emission efficiency from 2009 to 2018.

As shown in Figure 2, the more realistic real value of carbon emission efficiency is obtained by excluded the influence of internal, external, and random factors after processing raw data. It is found that although the first stage is affected by various factors, only preliminary data can be obtained from the traditional DEA model. Compared with average carbon emission efficiency in the third stage, carbon emission efficiency in the whole country has little change; carbon emission efficiency in the east is still the highest, reaching 0.877, the middle reaches 0.808, and it is still the lowest in the west, with an average carbon emission efficiency of 0.617. By comprehensively comparing the first stage and the third stage, it can be found that China's carbon emission efficiency is spatially distributed as a whole. The carbon emission efficiency of Eastern China is significantly higher than that of Western China. With the increase of years, the carbon emission efficiency of Eastern China is gradually opening up the gap with that of Western China. Akbar et al. also showed that although the east region is more densely populated, more developed in industry and commerce, and had more carbon emissions than the central and west regions, the eastern region of China has significantly higher carbon emission efficiency than central and western regions, because of its higher scientific, technological, and informatization levels [57].

As can be seen from Table 5, excluded the influence of environmental impact factors, and other random factors, the carbon emission efficiency of the third stage is significantly different from the first stage. The carbon emission efficiency of Inner Mongolia is still at the forefront of China, while other provinces and cities have changed. Among them, Beijing's carbon emission efficiency has decreased from 1.000 to 0.959, mainly caused by the decline in the scale and efficiency of Beijing. As a megacity, Beijing has many enterprises and factories, and it must formulate related carbon emission supervision policies to control the carbon emissions of enterprises [58]. Hainan's carbon emission efficiency dropped the most, from 0.975 to 0.361. In addition, the carbon emission efficiency of Liaoning, Jiangsu, Shandong, and Guangdong ranks first in China. The provinces with rising carbon emission efficiency include Hebei, Shanxi, Liaoning, Zhejiang, Shan, Henan, Hunan, Guangdong, and Sichuan. It shows that the carbon emission efficiency of these provinces, in the first stage, is disturbed by external factors. The provinces with reduced carbon emission efficiency include Beijing, Tianjin, Jilin, Heilongjiang, Shanghai, Anhui, Fujian, Jiangxi, Guangxi, Hainan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. This indicates that the previous high efficiency of these provinces is related to certain external influence factors, rather than the actual situation.

Table 5. The first stage efficiency and the third stage efficiency are used for comparison.

The First Stage				The Third Stage			
Area	**Carbon Emission Efficiency**	**Pure Technical Efficiency**	**Scale Efficiency**	**Area**	**Carbon Emission Efficiency**	**Pure Technical Efficiency**	**Scale Efficiency**
Beijing	1.000	1.000	1.000	Beijing	0.959	1.000	0.959
Tianjin	0.992	0.998	0.990	Tianjin	0.747	1.000	0.747
Hebei	0.839	0.859	0.976	Hebei	0.883	0.909	0.972
Shanxi	0.985	0.998	0.987	Shanxi	0.993	0.998	0.995
Nei Monggol	1.000	1.000	1.000	Nei Monggol	1.000	1.000	1.000
Liaoning	0.992	1.000	1.000	Liaoning	1.000	1.000	1.000
Jilin	0.877	0.878	0.980	Jilin	0.713	0.957	0.745
Heilongjiang	0.821	0.834	0.964	Heilongjiang	0.761	0.929	0.818
Shanghai	0.992	1.000	1.000	Shanghai	0.928	1.000	0.928
Jiangsu	0.986	1.000	0.988	Jiangsu	1.000	1.000	1.000
Zhejiang	0.891	0.913	0.969	Zhejiang	0.913	0.952	0.959
Anhui	0.834	0.905	0.912	Anhui	0.800	0.957	0.837
Fujian	0.865	0.869	0.972	Fujian	0.817	0.946	0.864
Jiangxi	0.819	0.838	0.955	Jiangxi	0.669	0.939	0.711
Shandong	0.965	1.000	0.973	Shandong	1.000	1.000	1.000
Henan	0.775	0.814	0.923	Henan	0.852	0.918	0.929
Hubei	0.761	0.765	0.953	Hubei	0.958	0.899	0.844
Hunan	0.693	0.708	0.934	Hunan	0.728	0.857	0.848
Guangdong	0.857	1.000	0.846	Guangdong	1.000	1.000	1.000
Guangxi	0.715	0.720	0.946	Guangxi	0.634	0.876	0.723
Hainan	0.975	1.000	0.983	Hainan	0.361	1.000	0.361
Chongqing	0.696	0.675	0.974	Chongqing	0.592	0.875	0.677
Sichuan	0.616	0.619	0.928	Sichuan	0.669	0.755	0.887
Guizhou	0.739	0.756	0.947	Guizhou	0.625	0.892	0.700
Yunnan	0.608	0.609	0.944	Yunnan	0.578	0.801	0.720
Shaanxi	0.961	0.967	0.986	Shaanxi	0.903	0.979	0.922
Gansu	0.714	0.712	0.971	Gansu	0.569	0.883	0.645
Qinghai	0.524	1.000	0.477	Qinghai	0.247	1.000	0.247
Ningxia	0.999	1.000	0.997	Ningxia	0.588	1.000	0.588
Xinjiang	0.807	0.821	0.991	Xinjiang	0.764	0.895	0.855
Average value	0.843	0.875	0.949	Average value	0.775	0.941	0.816

Based on the data excluding random factors and environmental factors in the third stage, the carbon emission efficiency values of 0.9 and 0.6 are set as critical points. The 30 provinces and cities are classified according to carbon emission efficiency: carbon emission efficiency is greater than 0.9 in areas of high efficiency; with medium efficiency between 0.6 and 0.9; and in those below 0.6 they are low efficiency areas (see Table 6).

From Table 6, it can be seen that several provinces in high-efficiency areas have high pure technical efficiency and scale efficiency, so that the overall comprehensive carbon emission efficiency is not low. Economic development in most provinces is in good shape; a few economically underdeveloped areas, such as Inner Mongolia, have maintained high carbon emission efficiency. That is because since the 21st century, the rapid economic growth of Inner Mongolia has laid a solid foundation for the improvement of local carbon emission efficiency [59]. Tianjin and Xinjiang are reduced from being original high-efficiency areas to medium efficiency areas. In Tianjin, in recent years, economic growth is slowing down, but energy consumption remains large. Large resource consumption is not supported by a matching economy, which leads to the decline of scale efficiency and affects overall carbon emission efficiency. The low carbon emission efficiency of Xinjiang is because Xinjiang develops its economy mainly by mining coal resources and simple processing of products, with a large proportion of secondary industry and insufficient investment in science and technology. The low-efficiency areas are Hainan, Gansu, Yunnan, Chongqing, Qinghai, and Ningxia. Most of these are underdeveloped areas, but their technical efficiency are high, which shows that these regions pay more attention to the development of science and technology, but their overall carbon efficiencies are affected by efficiency of scale.

Table 6. Classification of carbon emission efficiency values in Phase III.

High Efficiency Area	Beijing	Shanxi	Nei Monggol	Liaoning
	Shaanxi	Hubei	Zhejiang	Shandong
	Shanghai	Guangdong	Jiangsu	
Medium Efficiency Area	Tianjin	Hebei	Jilin	Henan
	Jiangxi	Guangxi	Sichuan	Guizhou
	Heilongjiang	Xinjiang	Anhui	Hunan
Low Efficiency Area	Hainan	Chongqing	Yunnan	Gansu
	Qinghai	Ningxia		

4. Conclusions and Suggestions

4.1. Conclusions

This paper studied the carbon emission efficiency of 30 provinces and cities in China, from 2009 to 2018. The significance of this paper is the introduction of three stages of the DEA method to calculate regional carbon emission efficiency, while analyzing the influencing factors of carbon emission efficiency in different regions of China. Our conclusions are as follows: (1) There is a significant difference between the first stage and the third stage of carbon efficiency; carbon emission efficiency of most regions in the third stage decreased by about 10%, compared with carbon emission efficiency in the first stage. Hainan, with the largest decline, decreased from 0.975 to 0.361, but the carbon emission efficiency of a few regions has increased by about 5%. (2) China's carbon emission efficiency is not completely synchronized with economic development; carbon emission efficiency of some underdeveloped regions has reached more than 0.9, while carbon emission efficiency of some provinces in eastern and central regions are far lower than carbon emission efficiency in some underdeveloped regions. (3) China's carbon emission efficiency is constrained by scale efficiency; when scale efficiency decreases by 10%, its carbon emission efficiency also decreases by 5–10%. (4) On the whole, China's carbon emission efficiency shows an upward trend, but the speed is relatively slow, so there is still much room for improvement.

4.2. Suggestions

Based on the research findings of this paper, the following suggestions are put forward: (1) Establish a carbon emission efficiency monitoring system network, which can control carbon emissions below the peak, and restrain carbon emissions. Relying on internet technology, establish a carbon emission efficiency monitoring network covering the whole country, detecting carbon emission efficiency in real-time. (2) Expand the channels of talent introduction and increase investment in technology. Technological innovation is an essential driving force of carbon emission reduction. Talent introduction and improvement of carbon emission technical efficiency can help to improve overall carbon emission efficiency [60]. (3) Local governments should make breakthroughs in the previously established emission reduction system. On the one hand, increasing the price of industrial energy, encouraging consumers to use clean energy and new energy that does not produce carbon dioxide emissions, then establishing a low-carbon environmental incentive mechanism in production and consumption. On the other hand, controlling the use of industrial energy and carbon dioxide products, strengthening the publicity of low-carbon environmental protection, and making people aware of the harm of carbon dioxide to preserve the environment, so that people can consciously protect the environment and reduce daily carbon dioxide emissions. It also needs to promote carbon taxes, limit carbon emissions, develop carbon trading licensing mechanisms, limit unscrupulous carbon dioxide emissions, and strictly regulate them [61].

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