Frontiers in Business, Economics and Management
ISSN: 2766-824X | Vol. 5, No. 1, 2022

Evaluation of the Development Efficiency of China's Regional Low-Carbon Economy Based on Three-Stage DEA Model

Jiaxin Mei[1, a]

[1]Nanjing University of Finance and Economics, Nanjing, Jiangsu Province 210023, China
[a]Email: fiftyjjj321@163.com

Abstract: With the goal of achieving carbon peak by 2030, it is necessary to objectively and correctly evaluate the development efficiency of low-carbon economy in China's provinces and municipalities. Starting from a review of the existing relevant literature, this paper uses a three-stage DEA Model, incorporating elements of the degree of low-carbon human development into external environmental variables, to conduct an empirical study of the development efficiency of low-carbon economy in 30 provinces and municipalities in China from 2017 to 2019. It is found that environmental factors such as the ratio of tertiary industry to secondary industry output, the intensity of R&D investment, and per capita disposable income had an impact on the evaluation results. After excluding external environmental factors and random errors, the overall low-carbon economic development level has improved, but there is still room for improvement of 29%. In particular, pure technical efficiency is underestimated, while scale efficiency is overestimated. In addition, regional differences are evident, with a pattern of "East China > Central China > Southwest China > North China = South China > Northeast China > Northwest China", which is basically consistent with the three-year average GDP ranking of each region.

Keywords: Low-Carbon Economy, Efficiency, Three-Stage Dea Model.

1. Introduction

Global warming has become one of the biggest challenges threatening to human development, and tackling climate change is an inevitable requirement for sustainable development.After the ratification of the Paris Agreement in 2016, achieving carbon neutrality has become a global agenda [1], and has greatly advanced the global practice of transitioning to a low-carbon economy and seeking green growth.

Since General Secretary Xi Jinping put forward the concept of new normal development in 2014, low-carbon transformation has become one of the key objectives of China's economic development [2].As the country with the highest carbon emissions in the world, China plays a crucial role in the global carbon peak and carbon neutrality [3].In 2020, China announced at the UN General Assembly that it aims to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060.

At a relatively low level of development, it is crucial for China to improve the development efficiency of the low-carbon economy to achieve the core goal of reaching a carbon peak by 2030.Therefore, it is necessary and urgent to objectively and correctly evaluate the development efficiency of low-carbon economy in China's provinces and municipalities.

The three-stage DEA model fully considers the impact of environmental factors and random errors on the management efficiency of production units, and can more objectively reflect the actual development efficiency of low-carbon economy in each province and region.Therefore, this paper uses the three-stage DEA model to evaluate the efficiency of low-carbon economic development in 30 provinces and municipalities in China (except Tibet) from 2017 to 2019, and on this basis, analyses the characteristics of low-carbon economic development efficiency in each region and the development differences between regions, with a view to providing theoretical guidance and implementation paths for the subsequent more efficient low-carbon economic development in China's regions, narrowing the gap in the level of low-carbon economic development between regions and further realising synergistic development.

2. Literature Review

The research of low-carbon economy evaluation index system is carried out relatively late, and influential research results are relatively few. On the basis of exploring the concept of low-carbon economy, the core elements and evaluation principles that should be included, domestic scholars such as Fu Jiafeng [4] constructed an indicator system to measure the development level of low-carbon economy from five dimensions: output, consumption, resources, policies and environment, and elaborated the corresponding evaluation methods, but lacked practical application. On this basis, Zhuang Guiyang et al. [5] further set corresponding thresholds or qualitative descriptions to the core indicators based on the perspective of guiding practice, and set evaluation criteria in both relative and absolute terms. This system is widely recognised, but its shortcoming is that it is rather macroscopic. In the situation of China's economic development transition to low-carbon under the new normal, Liu Tiansen and Zhu Yue [2] constructed a four-level evaluation index system according to the characteristics of the stage and the coordination of carbon productivity and human development that low-carbon economy has, namely the stage of low-carbon economic development, the degree of low-carbon human development, the level of low-carbon technology and the low-carbon policy environment.

In terms of empirical application, scholars have used different methods to evaluate the development efficiency of low-carbon economy based on different regional scales. Yang Ying [6] used the traditional DEA method to evaluate the development efficiency of low-carbon economy in Sichuan Province during the Eleventh Five-Year Plan period, concluding that the province's sloppy economic growth had not yet been transformed. Guo Jianhua [7] improved the traditional static TOPSIS method and evaluated the competitiveness of low-carbon economies between regions. Zheng Baohua [8] et al. evaluated China's low-carbon economic efficiency in 2015 using a three-stage DEA model and found that the government's environmental expenditure did not have a significant impact on low-carbon efficiency. Mu Liying and Xu Na [9] used the super-efficiency DEA method to evaluate the efficiency of low-carbon economic development in the Beijing-Tianjin-Hebei region from 2016 to 2018 and analysed relative efficiency, input redundancy and output deficiency.

The existing literature on low-carbon economy provides important insights for the conduct of this study. Although there are a few studies on the efficiency of low-carbon economy development at the provincial level in China using the three-stage DEA model: 1) The data selected were from an earlier period and the evaluation of the development efficiency of low-carbon economy in the 13th Five-Year Plan period is still blank. 2) The measurement of the degree of human development was neglected. The low-carbon economy is an organic coordination of carbon productivity and human development, therefore, human development is an important factor that cannot be ignored in influencing the efficiency of a low-carbon economy[2]. 3) The analysis of the differences between regions in China is limited to the East, Central and West, which is too general to clearly analyse the gaps that exist between regions. To this end, based on China's low-carbon economic evaluation index system under the new normal scenario proposed in the literature [2], this paper will evaluate the development efficiency of low-carbon economy of China's 30 provinces and municipalities with the data from 2017 to 2019 through a three-stage DEA model, with a view to objectively and correctly assessing the low-carbon economic development efficiency of China's provinces and municipalities, so as to provide reference for the achievement of the 2030 carbon peak target and subsequent practice.

3. Research Method and Data Description

3.1. The Basic Steps of the Three-stage DEA Model

3.1.1. The First Stage: DEA-BCC Model

In 1984, Banker, Charnes, and Cooper proposed the BCC model in "Management Science". The specific model is as follows:

There are n DMUs, each with m inputs and s outputs, for a particular DMU, as follows:

$$\begin{aligned} &\max(\mu^T y_0 - \mu^0) \\ &s.t.\omega^T x_j - \mu^T y_j + \mu_0 \ge 0 \\ &\omega^T x_0 = 1 \\ &\omega \ge 0, \mu \ge 0, j = 1,\dots,n. \end{aligned} \tag{1}$$

The dual programming of linear programming (1) is

$$\begin{aligned} &\min \theta \\ &s.t.\sum_{j=1}^{n} x_j\lambda_j \le \theta x_0 \\ &\sum_{j=1}^{n} y_j\lambda_j \ge y_0 \\ &\sum_{j=1}^{n} \lambda_j = 1 \\ &\lambda_j \ge 0, j = 1,\dots,n. \end{aligned} \tag{2}$$

The BCC model with a non-Archimedean infinitesimal ε is:

$$\begin{aligned} &\min\left[\theta - \varepsilon\left(e^T s^- + \hat{e}^T s^+\right)\right] \\ &s.t.\sum_{j=1}^{n} x_j\lambda_j + s^- = \theta x_0 \\ &\sum_{j=1}^{n} y_j\lambda_j - s^+ = y_0 \\ &\sum_{j=1}^{n} \lambda_j = 1 \\ &\lambda_j \ge 0, j = 1,\dots,n. \\ &s^+ \ge 0, s^- \ge 0 \end{aligned} \tag{3}$$

This paper selects the input-oriented BCC model to evaluate and analyze the decision unit from the perspective of technology and scale, respectively. Fried [10] suggests that the performance of decision-making units is influenced by management inefficiencies, environmental factors, and statistical noise. Therefore, the separation is needed.

3.1.2. 3.2.2 The Second Stage: SFA Model

In the evaluation research of the decision unit operation efficiency, it is often necessary to estimate the production function or the cost function. Suppose that the output of the decision unit i is:

$$y_i = f(x_i, \beta)\xi_i \tag{4}$$

In Formula (3.4), β is unknown parameter, ξ_i is the level of the decision unit i, satisfying $0 < \xi_i \le 1$. If $\xi_i = 1$, The decision unit i is just at the forefront of efficiency. Taking stochastic influences into account, the equation (4) is rewritten as:

$$y_i = f(x_i, \beta)\xi_i e^{v_i} \tag{5}$$

$e^{v_i} > 0$ is the effect of random factor. Equation (5) means that the front edge of the production function is stochastic, so such models are collectively called the "Stochastic Frontier Analysis", or the SFA.

Assuming $f(x_i,\beta)=e^{\beta_0}x_{1i}^{\beta_1}B\ x_{ki}^{\beta_k}$ has a total of K inputs, then taking the logarithm of both sides of equation (5):

$$ln\,y_i=\beta_0+\sum_{k=1}^{K}\beta_k\,ln\,x_{ki}+ln\,\xi_i+\nu_i \tag{6}$$

Due to $0<\xi_i\le 1$, so $ln\,\xi_i\le 0$ .Assuming $u_i=-ln\,\xi_i\ge 0$, The equation (6) can be written as:

$$ln\,y_i=\beta_0+\sum_{k=1}^{K}\beta_k\,ln\,x_{ki}+\nu_i-u_i \tag{7}$$

$u_i\ge 0$ is Inefficient item, it represents the distance between the decision unit i and the efficiency front edge. The distribution of mixed perturbation term $\varepsilon_i=\nu_i-\mu_i$ is asymmetry, so the inefficient terms u_i cannot be estimated by the OLS, Only assumptions can be made on the distribution of the ν_i、μ_i, and to perform a more efficient MLE.

Most efficiency evaluations in the empirical studies use a semi-normal distribution. SFA estimation of the cost function is very simple, similar to the deduction of the stochastic frontier model of the production function:

$$ln\,c_i=\beta_0+\beta_y\,lny_i+\sum_{k=1}^{K}\beta_k\,ln\,P_{ki}+\nu_i+u_i \tag{8}$$

where c_i is the cost of the decision unit i, y_i is the output, P_{ki} is the price of factor K, u_i is inefficiency terms, ν_i is the influence of random factors on the cost function. Based on the SFA theoretical analysis above, this paper selects the SFA cost function model, and the test method adopts a one-sided generalized likelihood ratio.

3.1.3. The Third Stage: Adjusted DEA Model

Fried [10] pointed out that the traditional DEA model needs to eliminate environmental factors and random errors by introducing the SFA model, and the adjusted input values and the original output values are then measured by the BCC model again. The contents of these three stages come together to become a three-stage DEA model, which can obtain efficiency values more objectively and accurately.

3.2. Variable Selection and Data Sources

3.2.1. Selection of Input-output Variables

Combined with the relevant literature and data, the following input and output indicators were selected. Given that low-carbon economic development efficiency seeks to produce more economic aggregate with fewer factor inputs while taking into account energy consumption and carbon emissions [8], GDP is chosen as the desired output indicator for efficiency evaluation and CO2 emissions as the undesired output indicator. Investment indicators include capital, labor and energy input. Since there is no direct statistical data of capital input, this paper estimates the capital stock according to the general practice, and it is obtained through the perpetual inventory method proposed by Shan Haojie [11]. Labour input is expressed as the quantity of employment at the end of the year in each province and municipality. Energy input is then measured as total energy consumption. As there are no official statistics on carbon dioxide emissions, this paper uses the formula in the IPCC Guidelines for National Greenhouse Gas Inventories[12] to calculate carbon dioxide emissions for the period 2017-2019 for each region based on the consumption of various types of energy published in the statistical yearbooks of each region.

3.2.2. Selection of External Environment Variables

After considering the characteristics of low-carbon economic development with the focus of this paper, external environmental variables are selected as follows.

As the optimisation of industrial structure plays an important role in the harmonious development of economy and environment, and the secondary industry is an important factor influencing the level of regional carbon dioxide emissions, the ratio of output value of the tertiary to the secondary industry is chosen to measure the impact of industrial structure on the efficiency of low-carbon economic development.

As the level of technology affects the development process of low-carbon economy from different areas, the development of technology is an important support for the improvement of carbon productivity[13], therefore, this paper uses the of R&D investment intensity to measure the support of local governments for the level of technology.

As an economic form, low-carbon economy is an organic coordination between carbon productivity and human development, therefore, human development is an important factor affecting the efficiency of low carbon economy. Referring to the construction of the indicator layer in the low-carbon human development degree by Liu Tiansen [2], this paper chooses per capita disposable income as the indicator to measure the human development degree.

3.2.3. Data Sources

To ensure the consistency and accuracy of the data, all the data in this paper are from the China Statistical Yearbook and statistical yearbooks of provinces and municipalities. Due to the absence of some data from Tibet Autonomous Region, the remaining 30 provinces and municipalities in China (excluding Hong Kong, Macao and Taiwan) are taken as the subject of this paper.

4. Empirical Analysis

4.1. DEA Analysis of the First Stage

Considering that carbon dioxide is an undesirable output, a preliminary analysis of the efficiency of low-carbon economic development in 30 provinces and municipalities in China from 2017 to 2019 was conducted by MaxDEA8 software, as shown in Table 1. It can be seen from Table 1 that under the measurement of the traditional DEA method, the overall efficiency level of China's low-carbon economic development is low, and there is great room for improvement. From the whole perspective of three years, China's regional comprehensive technical efficiency is 0.66, average pure technical efficiency is 0.77, average scale efficiency is 0.87. Average pure technical efficiency is low, indicating that management and technology have not been given full play in the process of low-carbon economic development in China. From the perspective of provinces and regions, only Beijing achieved effective comprehensive efficiency in 2017,2018 and 2019, with the rest of the regions having varying degrees of room for improvement in pure technical efficiency and scale efficiency, of which the lowest comprehensive technical efficiency was in Qinghai at 0.35.

In addition, from 2017 to 2019, the comprehensive technical efficiency, pure technical efficiency and scale efficiency of China's regional low-carbon economic development all showed a certain downward trend. However, due to environmental factors and random errors, this result is not yet an objective and realistic reflection of China's low-carbon economic development, and further adjustment is needed.

Table 1. Low-carbon economic development efficiency in the first stage

	2017			2018			2019		
DMU	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tianjin	0.92	1.00	0.92	0.86	0.96	0.90	0.57	0.73	0.78
Hebei	0.63	0.64	0.98	0.61	0.62	0.98	0.50	0.50	1.00
Shanxi	0.63	0.69	0.91	0.65	0.71	0.92	0.58	0.65	0.89
Inner Mongolia	0.54	0.62	0.88	0.54	0.62	0.88	0.49	0.58	0.84
Liaoning	0.53	0.54	0.98	0.56	0.57	0.98	0.49	0.51	0.95
Jilin	0.55	0.63	0.87	0.52	0.62	0.84	0.34	0.52	0.66
Heilongjiang	0.54	0.59	0.92	0.52	0.57	0.91	0.37	0.44	0.84
Shanghai	0.99	1.00	0.99	0.97	1.00	0.97	1.00	1.00	1.00
Jiangsu	0.92	1.00	0.92	0.91	1.00	0.91	0.82	1.00	0.82
Zhejiang	0.95	1.00	0.95	0.94	1.00	0.94	0.86	0.99	0.87
Anhui	0.79	0.80	1.00	0.79	0.79	1.00	0.80	0.81	0.98
Fujian	0.66	0.70	0.95	0.65	0.72	0.91	0.69	0.75	0.92
Jiangxi	0.84	0.88	0.96	0.83	0.86	0.96	0.77	0.81	0.95
Shandong	0.72	0.77	0.93	0.70	0.76	0.92	0.56	0.66	0.85
Henan	0.54	0.62	0.86	0.53	0.63	0.84	0.51	0.64	0.79
Hubei	0.73	0.75	0.98	0.72	0.74	0.97	0.68	0.74	0.93
Hunan	0.80	0.82	0.98	0.78	0.80	0.98	0.71	0.73	0.96
Guangdong	0.92	1.00	0.92	0.89	1.00	0.89	0.80	1.00	0.80
Guangxi	0.52	0.55	0.94	0.54	0.57	0.95	0.49	0.52	0.93
Hainan	0.62	1.00	0.62	0.62	1.00	0.62	0.60	1.00	0.60
Chongqing	0.81	0.85	0.95	0.76	0.80	0.95	0.73	0.77	0.94
Sichuan	0.82	0.85	0.97	0.82	0.85	0.96	0.78	0.84	0.92
Guizhou	0.67	0.75	0.89	0.62	0.70	0.89	0.57	0.64	0.88
Yunnan	0.48	0.52	0.92	0.46	0.50	0.93	0.48	0.51	0.94
Shaanxi	0.67	0.69	0.97	0.67	0.69	0.97	0.59	0.61	0.96
Gansu	0.60	0.79	0.76	0.63	0.82	0.77	0.58	0.79	0.73
Qinghai	0.36	1.00	0.36	0.36	1.00	0.36	0.32	1.00	0.32
Ningxia	0.41	0.96	0.42	0.40	0.98	0.40	0.39	1.00	0.39
Xinjiang	0.46	0.55	0.84	0.48	0.57	0.85	0.46	0.55	0.83
Mean	0.69	0.79	0.88	0.68	0.78	0.88	0.62	0.74	0.84

4.2. Regression Analysis of SFA in the Second Stage

The SFA regression results obtained by taking the data derived from the first stage and using the software Frontier 4.1 are shown in Table 2. As can be seen from Table 2, the regression coefficients of each external environmental variable on each input slack variable all reach 1% significance level, indicating that the selected external environmental factors have a significant impact on the redundancy of low-carbon economic inputs in various regions. In addition, the γ value is close to 1 and reach 10% and 1% significance levels respectively, indicating that the influence of management factors dominates among the inputs and plays an important role in the efficiency of low-carbon economic development. This result illustrates the need for a stripping analysis of management factors and random factors. Therefore, the coefficients of each environmental factor on the input slack variables are further examined.

The ratio of the output value of the tertiary to secondary industry has a negative regression coefficient for/of??? the slack variables of capital stock and total energy consumption, which shows that the optimization and upgrading of industrial structure plays a positive role in promoting the reduction of capital consumption and total energy consumption. This is consistent with the actual situation. In recent years, China has further promoted the optimization and upgrading of the industrial structure, developing the tertiary industry and regulating the development of energy-intensive industries, one of the effects of which is to obtain greater economic benefits with less energy input. The regression coefficient of this variable on the slack variables of employment number is positive, indicating that the optimization of industrial structure needs more manpower. But on the other hand, the development of the tertiary industry helps to promote employment and alleviate the current employment difficulties.

Per capita disposable income, as an index to measure the degree of regional human development, has a negative relationship with the slack variables of capital stock, employment and total energy consumption, indicating that the higher the per capita disposable income, the less waste of investment, which is a quality environmental factor.

The intensity of R & D investment is positively correlated with the slack variables of capital stock and employment, and negatively correlated with total energy consumption, indicating that increasing technology input is effective for the reduction of energy consumption, but requires a large amount of manpower and capital. Therefore, while maintaining the rapid growth of R&D investment intensity, the effective allocation of funds must also be realized.

Based on the above analysis, it is likely that regions in different external environments will show large deviations in the development efficiency of low-carbon economy due to the effect of the external environment, as each environmental factor has a different impact on the input slack variables in regional low-carbon economic development. Therefore, it is necessary to adjust the original input variables and examine the true level of efficiency of each region.

Table 2. SFA regression results

	Capital stock slack variable		Employment slack variable		Total energy consumption slack variable	
	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio
Constant term	9459.913	9459.913***	597.585	4.5045***	4294.331	4294.331***
Ratio of output value of the tertiary to the secondary industry	-3651.675	-3651.675***	257.254	4.227***	-1194.739	-1194.739***
Per capita disposable income	-2105.541	-2105.541***	-580.409	-64.281***	-732.682	-732.682***
R&D investment intensity	250.125	250.125***	288.728	7.375***	-521.421	-521.421***
σ2	407936480.000	407936480.000***	1482563.600	1479312.000***	81581154.000	81581154.000***
γ	0.967	1.912*	0.991	615.171***	0.977	1.945*
log	-903.471		-628.220		-823.717	
LR	149.313***		194.254***		163.964***	

Table 3. Low-carbon economic development efficiency in the third stage(after adjusting the input variables)

	2017			2018			2019		
DMU	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tianjin	0.67	0.95	0.70	0.63	0.92	0.68	0.47	0.75	0.64
Hebei	0.70	0.75	0.93	0.69	0.74	0.93	0.62	0.67	0.93
Shanxi	0.66	0.87	0.76	0.69	0.92	0.76	0.69	0.88	0.79
Inner Mongolia	0.49	0.66	0.74	0.48	0.68	0.71	0.46	0.66	0.71
Liaoning	0.57	0.71	0.80	0.61	0.74	0.81	0.59	0.71	0.83
Jilin	0.75	1.00	0.75	0.71	1.00	0.71	0.49	0.84	0.58
Heilongjiang	0.53	0.75	0.72	0.52	0.73	0.71	0.43	0.65	0.65
Shanghai	0.78	0.88	0.88	0.78	0.88	0.89	0.83	0.89	0.93
Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zhejiang	0.97	1.00	0.97	0.99	1.00	0.99	1.00	1.00	1.00
Anhui	0.87	0.96	0.90	0.87	0.96	0.92	0.96	1.00	0.96
Fujian	0.90	1.00	0.90	0.91	1.00	0.91	0.96	1.00	0.96
Jiangxi	0.86	1.00	0.86	0.87	1.00	0.87	0.91	1.00	0.91
Shandong	0.81	0.82	0.99	0.80	0.81	0.99	0.71	0.72	0.98
Henan	0.78	0.83	0.94	0.78	0.82	0.94	0.82	0.84	0.98
Hubei	0.81	0.89	0.90	0.82	0.91	0.90	0.86	0.93	0.92
Hunan	0.87	0.94	0.93	0.86	0.93	0.93	0.86	0.91	0.95
Guangdong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Guangxi	0.66	0.84	0.79	0.67	0.86	0.79	0.61	0.80	0.77
Hainan	0.37	1.00	0.37	0.38	1.00	0.38	0.40	1.00	0.40
Chongqing	0.82	1.00	0.82	0.80	1.00	0.80	0.86	1.00	0.86
Sichuan	0.90	0.97	0.93	0.92	0.99	0.93	0.95	0.99	0.96
Guizhou	0.70	0.96	0.73	0.68	0.92	0.74	0.68	0.87	0.77
Yunnan	0.55	0.73	0.74	0.55	0.74	0.75	0.62	0.78	0.79
Shaanxi	0.75	0.91	0.82	0.76	0.93	0.82	0.73	0.88	0.83
Gansu	0.53	1.00	0.53	0.57	1.00	0.57	0.59	1.00	0.59
Qinghai	0.23	1.00	0.23	0.23	1.00	0.23	0.23	1.00	0.23
Ningxia	0.29	1.00	0.29	0.29	1.00	0.29	0.29	1.00	0.29
Xinjiang	0.49	0.78	0.63	0.52	0.81	0.65	0.54	0.79	0.68
Mean	0.71	0.91	0.79	0.71	0.91	0.79	0.71	0.88	0.80

4.3. DEA Analysis After the Adjustment of Input Variables in the Third Stage

Adjusting the input variables and substituting the adjusted input values into the BCC model again together with the original output values, the low-carbon economic development efficiency of 30 provinces and municipalities in China in the third stage was obtained, as shown in Table 3. Compared with the results of the first stage, after excluding the influence of environmental factors and random errors, the development efficiency of low-carbon economy in various regions has changed greatly.

The three-year average national comprehensive technical efficiency rose from 0.66 to 0.71(up 5%).This was mainly due to an increase in the average pure technical efficiency, which rose from 0.77 to 0.90(up 13%), but the average scale efficiency fell from 0.87 to 0.79. At this stage, the overall development level of low-carbon economy in China has improved, indicating that it was underestimated under the influence of external environmental factors and random errors in the first stage. It can be seen that the previous low pure technical efficiency is mainly caused by poor external environmental factors, rather than the backward management and technical level. But the scale efficiency is overestimated. At the regional level, the number of provinces achieving effective comprehensive efficiency for three years has increased, not only Beijing, but also Jiangsu and Guangdong. Compared with the first stage, both Jiangsu and Guangdong were effective due to the increase of scale efficiency. In addition, in 2019, Zhejiang province also reached effectiveness. Meanwhile, the three-year average value of comprehensive efficiency in 22 regions showed varying degrees of increases compared to the first stage, while seven provinces and cities, namely Tianjin, Inner Mongolia, Shanghai, Hainan, Gansu, Qinghai and Ningxia, showed decreases, indicating that these regions are likely to be located in a more favourable external environment, thus leading to the previously overestimated efficiency. For the dynamic differences between the development efficiency of low-carbon economy in the first and third stages, in the third stage, the average comprehensive technical efficiency of China's regional low-carbon economic development was 0.71 in each year from 2017 to 2019, differing from the descending trend in the first stage. The average pure technical efficiency was 0.91, 0.91 and 0.88 from 2017 to 2019, the trend of which is nearly consistent with the previous results. The average scale efficiency was 0.79, 0.79 and 0.80. Contrary to the decline in 2019 in the first stage, there was a small rise in the scale efficiency in 2019 in the third stage. Overall, there is still around 29% of room to improve the development efficiency of China's low- carbon economy. Despite the three-year average national pure technical efficiency is 0.90, there is still 10% of room for development, so we should continue to increase management and technical innovation. The average value of scale efficiency is 0.79, combined with the fact that, except for the provinces and municipalities that have reached effectiveness, all other regions are in a state of increasing scale remuneration, indicating that the focus of the next stage of development is to enhance the development scale in each region and utilise its scale efficiency.

4.4. Analysis of Regional Differences in the Development Efficiency of Low-Carbon Economy in China

In this paper, China's provincial and municipal regions are divided according to a regional division method based on the seven regions of North China, Northeast China, East China, Central China, South China, Southwest China and Northwest China, as a way to comprehensively analyse regional differences in the development efficiency of low-carbon economy, as shown in Table 4. Due to the differences in historical environment and natural geography, the level of economic development and human development varies from region to region, resulting in obvious regional differences in the low-carbon economic development level.

Table 4. DEA Results of Low Carbon Economy in Seven Regions of China from 2017 to 2019

	2017			2018			2019		
DMU	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE
North China	0.70	0.85	0.83	0.70	0.85	0.82	0.65	0.79	0.81
Northeast China	0.62	0.82	0.75	0.61	0.82	0.74	0.50	0.73	0.69
East China	0.88	0.95	0.93	0.89	0.95	0.94	0.91	0.95	0.96
Central China	0.82	0.89	0.92	0.82	0.89	0.92	0.85	0.89	0.95
South China	0.68	0.95	0.72	0.69	0.95	0.72	0.67	0.93	0.72
Southwest China	0.74	0.91	0.81	0.74	0.91	0.80	0.78	0.91	0.85
Northwest China	0.46	0.94	0.50	0.48	0.95	0.51	0.48	0.93	0.53

In terms of the three-year average comprehensive technical efficiency, East China has the highest low-carbon economic development efficiency at 0.89, followed by Central China and Southwest China at 0.83 and 0.75, South China and North China both at 0.68, Northeast China and Northwest China ranked last at 0.58 and 0.47. It can be seen that the development efficiency of low-carbon economy in China shows a general pattern of "South > North". Furthermore, the ranking of each region is basically consistent with its GDP level. In terms of the three-year average pure technical efficiency and scale efficiency, East China is both in the lead, and its scale efficiency is increasing year by year. The lowest pure technical efficiency is in Northeast China at 0.79 and the lowest scale efficiency is in Northwest China at 0.51. Northeast China should pay more attention to the improvement of management and technology. In view of high pure technical efficiency, low scale efficiency is the main factor leading to low comprehensive technical efficiency in Northwest China, thus it should enlarge the development scale by expanding production in order to increase economic benefit and low carbon economic development efficiency.

On the whole, East China has been the most economically developed region in China in recent years, with a large inflow of talents, a high level of human development, advanced low-carbon technology and low-carbon concepts, and a number of advantages in the development efficiency of low-carbon economy. As an old industrial base, the north-eastern region has suffered a serious loss of population in recent years, and this loss has taken capital, technology and labour with it, seriously affecting the overall efficiency of low carbon economic development. The Northwest, with its harsh geographical circumstance and sparse populations, is at the bottom of the list due to its low level of economic development, low inputs and backward human development, even though its CO2 emissions are not high.

5. Brief Conclusions and Suggestions

Using a three-stage DEA model, this paper makes an evaluation of the development efficiency of low-carbon economy in 30 provinces and municipalities in China (excluding the Tibet Autonomous Region and Hong Kong, Macao and Taiwan) from 2017 to 2019, the conclusions and recommendations are as follows:

1)There are significant effects of external environmental factors and random errors on the development efficiency of low-carbon economy in China, with average comprehensive technical efficiency and pure technical efficiency being underestimated and scale efficiency being overestimated. From the results of the analysis of the three selected environmental factors, firstly, governments should continue to deeply adjust the industrial structure and further optimise and upgrade the industrial structure according to the concept of sustainable development. While refining the carbon peak implementation plan for key industries and sectors and curbing the blind development of high-emission industries, the support for the development of new industries such as new energy and biotechnology to grow green industries and achieve high-quality development should be increased. Secondly, further efforts to strengthen the intensity of investment in low-carbon technology research and development are needed, and the establishment of an effective mechanism to combine government, industry, academia and scientific research[14] to drive development through innovation should be accelerated. Finally, education on green, low-carbon and sustainable lifestyles should also be stepped up so that lead a popular trend in the whole society, moving towards a civilised development path of green production and people's prosperity [15].

2) All provinces and municipalities in China are basically in the stage of increasing returns to scale, indicating that the optimal scale has not yet been reached. Therefore, the scale of production should be further expanded and factor allocation should be adjusted to increase economic benefit and low carbon economic development efficiency.

3) From a regional perspective, there are significant differences in the development efficiency of low-carbon economy among the seven major regions in China, with a pattern of "East China > Central China > Southwest China > North China = South China > Northeast China > Northwest China". In the future transformation of low carbon development, emphasis should be placed on strengthening the exchange of talents and technologies between regions to narrow the gap between the efficiency of low carbon economic development in each region, so as to promote the improvement of the development efficiency of low carbon economy in China as a whole and ultimately achieve regional synergistic development.

References

[1] Murshed Muntasir, Ahmed Zahoor, Alam Md Shabbir, Mahmood Haider, Rehman Abdul, Dagar Vishal. Reinvigorating the role of clean energy transition for achieving a low-carbon economy: evidence from Bangladesh [J]. Environmental science and pollution research international, 2021, (28).

[2] Liu Tiansen, Zhu Yue. Research on the Construction of China's Low-carbon Economy Evaluation Index System under the Background of the New Normal [J].Modern Business Trade Industry, 2020, 41(35):16-18.(in Chinese)

[3] Hu Angang.China's carbon peak by 2030 target and its main ways [J].Journal of Beijing University of Technology（Social Sciences Edition）, 2021, 21(03):1-15. (in Chinese)

[4] Fu Jiafeng, Zhuang Guiyang, Gao Qingxian. Concept Identification and Evaluation Index System Construction of Low-Carbon Economy [J].China Population,Resources and Environment, 2010, 20(08):38-43. (in Chinese)

[5] Zhuang Guiyang, Pan Jiahua, Zhu Shouxian.The Connotation of the Low-Carbon Economy and the Construction of the Comprehensive Evaluation Index System [J].Economic Perspectives, 2011(01):132-136. (in Chinese)

[6] Yang Ying.Efficiency Evaluation of Low-Carbon Economy Development in Sichuan Province [J].China Population,Resources and Environment, 2012, 22(06):52-56. (in Chinese)

[7] Guo Jianhua. The efficiency evaluation of low carbon economic performance based on dynamic TOPSIS method [J]. Journal of Interdisciplinary Mathematics, 2017, 20(1).

[8] Zheng Baohua, Li Xiangqian, Huang Li.Research on China's Regional Low Carbon Economy Efficiency Based on Three-Stage DEA Model [J]. Journal of Anhui University of Technology（Social Sciences), 2017, 34(06):3-6. (in Chinese)

[9] Mu Liying, Xuna.Research on the Efficiency Evaluation of low-carbon economic development in Beijing-Tianjin-Hebei region based on ultra-efficiency DEA [J]. Journal of Hebei University of Science and Technology(Social Sciences), 2022, 22(01):12-18. (in Chinese)

[10] Fried HO, Lovell CA K, Schmidt S S, Yaisawarng S. Accounting for Environmental Effects and Statistical Noise in Data Envelopment Analysis[J]. Journal of Productivity Analysis, 2002, 17(1-2):157-174.

[11] Shan Haojie.Re-estimate of China's Capital Stock K: 1952-2006 [J]. The Journal of Quantitative & Technical Economics, 2008, 25(10):17-31. (in Chinese)

[12] IPCC. 2006 IPCC Guidelines for National Greenhouse Gas Inventories：volume II[R]. Japan：the Institute for Global Environmental Strategies，2008.

[13] Hu Dali, Ding Shuai. Research on the Evaluation Index System of Low Carbon Economy [J]. Science & Technology Progress and Policy, 2010, 27(22):160-164. (in Chinese)

[14] Liu Si, Tan Wenting. Research on Government Management in the Construction of Low-carbon Economy in Guangzhou[J]. Frontiers in Economics and Management, 2021, 2(6).

[15] Xi Jingping. To Win a Decisive Victory In Building a Moderately Prosperous Society In All Respects And Achieve The Great Victory Of Socialism With Chinese Characteristics For a New Era [N]. People's Daily, 2017-10-28(001). (in Chinese)