Advances in Economics, Business and Management Research, volume 85
2nd International Conference on Economy, Management and Entrepreneurship (ICOEME 2019)

Evaluation of Provincial Carbon Emission Reduction Efficiency Based on Three-stage DEA Model*

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***Abstract*—In recent years, the ecological and environmental governance in China has been significantly strengthened. Environmental conditions have been effectively improved, but at the same time, carbon dioxide emissions are still on the rise. Therefore, it is of great significance to evaluate the carbon emission reduction efficiency of Chinese provinces. And it is helpful to realize green and low-carbon development. This paper evaluated the carbon reduction efficiency of Chinese 30 provinces from 2014-2016 by building three stage DEA model, which put the energy consumption and carbon emissions as input variables and put the GDP as the expected output variables. Then this paper uses the SFA model to eliminate the effect of industrial structure, technology R&D and external environment factors. The results show that: first, the overall carbon emission reduction efficiency is low, only Beijing and Hainan province is effective; second, the level of economic development has an important impact on the regional carbon emission efficiency, which cause a huge difference in 30 provinces; third, the scale efficiency of carbon emission reduction is generally high, and the main reason of the lower carbon emission reduction efficiency is the low pure technology efficiency. Finally, the authors bring some suggestions from government and enterprises level: enterprises should improve their awareness of emission reduction, increase their investment in scientific research, and have a positive respond to government policies; the government should give consideration to the development of the eastern and western regions, adjust the energy structure and promote industrial upgrading. At the same time, government should actively establish a market-oriented emission reduction system to improve the carbon emission reduction efficiency.**

Keywords*—*carbon emission reduction efficiency; three-stage DEA; SFA regression

*Sponsors: National social science foundation project: "Study on the optimization of China's carbon trading mechanism from the perspective of political economy (17BJL123)";

Soft science foundation project of Shandong science and technology department: "Study on liquidity of carbon trading market in Shandong province (2018RKB01487)".

I. Introduction

The 19th CPC National Congress Report pointed out that people's demand for a better life has not only need higher requirements for material and cultural life, but also for democracy, rule of law, fairness, justice, security and the environment. China should follow the footsteps of global environmental governance, implement the emission reduction commitment made at the Copenhagen conference, and gradually build a green, low-carbon and sustainable economic system. As an important index, carbon emissions reduction efficiency can measure the relationship between energy input, economic growth and CO_2 emissions. So it is of great significance to evaluate provincial carbon emission reduction efficiency.

II. Literature Review

As the world's largest emitter of carbon dioxide, China has a huge task to cut carbon emissions. Since 2002, China's economy has entered a stage of rapid growth. The Kyoto protocol came into force in 2005, but as a non-annex I country,

China's carbon emissions have not been significantly affected and still maintain a trend of rapid growth. The carbon trading in China has mitigated the growth of carbon dioxide emissions since 2013. However, it should not be neglected that despite the continuous adjustment of industrial structure, improvement of energy efficiency and achievements in energy saving, fossil energy is still the main driving force of economic development. Therefore the research on carbon emission reduction efficiency has become the focus of scholars, which mainly focus on the following two aspects:

A. *Influence Factors of Carbon Emission Reduction Efficiency*

Through the total factor productivity index method, Tang Jianrong and Wu Lijuan (2013) made an inter-temporal

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dynamic analysis of carbon emission efficiency of six industries, and found that technological progress was the key factor to improve the carbon emission efficiency. Liu Xiang and Chen Xiaohong (2017) put carbon dioxide emissions as an unexpected output in the efficiency evaluation model. The empirical results showed that the energy-dependent industrial structure made Guizhou and Shanxi have the lowest carbon emission reduction efficiency from 2000 to 2012, and there is a large amount of redundancy in carbon dioxide emissions which means huge potential for emission reduction. Rong Xianbiao et al. (2016) examined the factors affecting the emission reduction efficiency of various cities in Hunan province through multiple regression analysis, and found that the advanced level of industry and government support are the key factors that affect the emission reduction efficiency. Deng Shanshan et al. (2016) found that GDP per capita can promote the growth of emission reduction efficiency, while the degree of industrialization will inhibit the efficiency of emission reduction. Meng Qingchun et al. (2016) built an econometric model and analyzed the factors affecting energy efficiency. The results showed that energy endowment, industrial structure and government influence were negatively correlated with energy efficiency, while technological progress was significantly positively correlated with energy efficiency. Wu Weihong et al. (2018) constructed a composite system model of technology innovation, energy saving and emission reduction efficiency in high energy-consuming industries. The empirical results showed that the coordinated development of technology innovation, energy saving and emission reduction efficiency had an obvious promoting effect on emission reduction efficiency of industrial enterprises.

B. Evaluation on Carbon Emission Reduction Efficiency at Provincial or Regional Level

Li Zhixue (2013) combined the analytic hierarchy process and data envelopment analysis to construct an evaluation index system of emission reduction efficiency, and made a comparative study on the emission reduction efficiency of 30 provinces in 2010. Zhang Jing and Wang Liping (2010) evaluated the industrial energy efficiency of Suzhou city from 1998 to 2008 by using the super-efficiency DEA model, and found that there are many redundant in energy inputs and the overall energy efficiency has a large gap. Zhang Jigang and Yang Hongjuan (2018) used the DDF-DEA three-stage model to evaluate the provincial emission reduction efficiency. The study found that the provincial emission reduction efficiency was significantly different, and only a few provinces were effective. The main reason was the lack of scale effect. Li Xin et al. (2017) evaluated the emission reduction efficiency of Chinese county-level sewage treatment through Dea-Tobit model, and found that the technical efficiency of sewage emission reduction and the load rate of reduction equipment was both low. Chen Xiaohong et al. (2017) analyzed the regional carbon emission efficiency of China from 2002 to 2012 based on the three-stage SBM-DEA, and found that although the overall emission reduction efficiency was low, it was still on the rise.

Based on the above literature, the research on China's carbon emission reduction efficiency has achieved certain results, which has a strong reference value. Therefore this paper makes the following innovations: First, carbon dioxide emissions are incorporated into the model as an input index. The process of energy consumption will inevitably produce exhaust emissions. Therefore, the goal of achieving the maximum GDP output with the minimum input can be met by adding carbon dioxide emissions into the model as an input index. Secondly, the SFA model is used to eliminate external environmental and random factors that may affect the output, which makes a more accurate evaluation of carbon emission reduction efficiency.

III. Research Design

A. Model Selection

The three-stage DEA model was proposed by Fried et al. (2002) which combined with the stochastic frontier analysis (SFA) method proposed by Aigner et al. (1977) in order to eliminate the impact of environment and random variables. The construction and application of this model include three stages, which can make the calculated results more truly reflect the efficiency level of the decision-making unit.

1) Stage 1:traditional DEA model (BCC model): Data Envelopment Analysis (DEA) was first proposed by Chaenes Cooper and Rhodes (1978) (CCR). The CCR model is an efficiency evaluation method for multiple input and output of multiple decision-making units on the premise of constant scale effect from the perspective of production function. Due to the assumption of constant scale effect, the relative efficiency calculated by CCR cannot reflect the scale reward. Banker et al. (1984) on the basis of CCR model further proposed the BCC model, which can decompose technical efficiency into pure technical efficiency and scale efficiency. Based on the traditional BCC model and referring to Hailu and Veeman's (2001) proposal, this paper regard the non-expected output as input so as to achieve the maximum GDP output with less carbon dioxide emissions. The model expression is as follows:

$$\theta^* = \max \theta$$

$$s.t.$$

$$\sum_{j}^{n} \lambda_j x_{ij} \le x_{io}, i = 1,2,3..., m$$

$$\sum_{j}^{n} \lambda_j y_{rj} \le y_{ro}, r = 1,2,3..., s$$

$$\sum_{j}^{n} \lambda_j = 1, \lambda_j \ge 0, \ \mathrm{j} = 1,2,3..., \mathrm{n}$$

“n/m/s” means the number of decision-making units, input indicators and output indicators in the model. DMU_0 refers to one of the decision making units to be evaluated. And x_{io} and y_{ro} represents the No.i input and the No.r output of the DMU_0, λ_j represents the weight, and θ* represents the optimal efficiency value.

2) Stage 2: stochastic frontier analysis model: The purpose of the second stage is to decompose the slacks of the first stage. The results of calculation and analysis in the first stage cannot accurately distinguish the external environmental and random variables on efficiency value, therefore, Fried, etc. (2002) build SFA model to strip the impacts of external environmental and random variable factors on the investment value.The constructor model is as follows:

$$S_{ni} = f^n(z_i;\beta_n) + v_{ni} + u_{ni}, n = 1,2...,N; i = 1,2...,I$$

S_{ni} is the slacks of the input of the Nth item of the Ith decision unit, $f^n(z_i;\beta_n)$ represents the determined feasible relaxation frontier, z_i represents the environmental variables, β_n represents the coefficient of environmental variables, and $v_{ni} + u_{ni}$ represents the error mixed term.

The input-output value was adjusted by SFA regression results, and the functional formula is as follows:

$$x_{ni}^A = x_{ni} + [\max(f(z_i,\beta_n)) - f(z_i,\beta_n)] + [\max(v_{ni}) - v_{ni}],$$
$$n = 1,2...,N; i = 1,2...,I$$

x_{ni}^A and x_{ni} respectively represents the amount of input after and before adjustment, $\max(f(z_i,\beta_n)) - f(z_i,\beta_n)$ represents the unified external environment, and $\max(v_{ni}) - v_{ni}$ represents that all DMU have the same luck.

3) Stage 3: the adjusted BCC model: In the third stage, the adjusted input data were substituted for the original input data, and the output was still the original output data. The BCC model was used again for evaluation. At this time, the efficiency value obtained was the one that excluded the influence of external environmental factors and random variables, which was more real and accurate.

The advantages of the three-stage DEA method are as follows: First, carbon dioxide emissions are incorporated into the model as input variables to achieve the maximum GDP output with the minimum input of carbon dioxide. The adjusted carbon dioxide emissions can provide a reference for the total carbon emissions set by various provinces when they participate in carbon trading market. Secondly, SFA model can effectively eliminate the influence of external environment, random variables and other factors on the efficiency evaluation results.

B. Index Construction and Data Analysis

Due to the availability and consistency of data, this paper excluded Tibet, Hong Kong, Macao and Taiwan, selected 30 provinces and cities from 2014 to 2016 as objects, took total energy consumption and carbon emissions as input indicators, and took total regional GDP as output indicators for analysis. The data were obtained from the national bureau of statistics website, China statistical yearbook, China energy statistical yearbook and statistical yearbooks of provinces and cities. The details are as follows:

1) Input index

a) Total energy consumption: The total energy consumption unit is ten thousand tons of standard coal, including raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, natural gas and electricity consumed by each province and city. Under the condition of constant energy consumption, the efficiency of emission reduction is the highest when the minimum carbon emission and the maximum GDP output are realized. Therefore, this paper only takes the total energy consumption as the input index without considering human resources, capital and other influencing factors.

b) Carbon emissions : The unit of carbon emission is ten thousand tons, and its calculation method is "carbon emission = various energy * standard coal conversion coefficient * carbon emission number". The calculation formula is based on the 2006 IPCC carbon dioxide emission calculation guidelines, and the standard coal conversion coefficient and carbon emission coefficient are all from China energy statistical yearbook. In the past, researchers mostly included carbon emission as output index into the model, but this paper tried to regard it as input index to study the amount of carbon emission in each city from the perspective of minimum input when realizing the maximum output and provide reference for the formulation of the total amount of national carbon market.

2) Output index: Total GDP: The output index selects the total annual GDP of the region, whose unit is 100 million yuan. DEA model does not directly process data, so no dimensionless processing is required for each index data.

In this paper, there are 30 decision making units, including two input indicators and one output indicator, which conform to the guiding principle of DEA model (Cooper William W, 2007), that the number of decision making units should be more than twice the number of input and output . Moreover, the value of each index is greater than zero, which conforms to the empirical formula of DEA evaluation.

3) Environmental index

a) The proportion of the tertiary industry: According to the data, the number of energy consumption of the second industry in our country accounts for 70% of the total energy consumption. Therefore, CO_2 emissions is mainly due to the industrial production. But with the transformation and upgrading of industrial enterprises in recent years, the added value of the third industry increased year by year, which has the characteristics of low pollution and high income. This paper selects the tertiary industry proportion as environment variables. The higher the proportion of the tertiary industry, the lower energy consumption and carbon emissions.

b) The proportion of R&D expenditure: Technological progress is the key to energy conservation and emission reduction. In the long run, the only effective way to reduce carbon emissions is to change the energy structure and improve the energy efficiency through technological progress (Li kaijie, qu ruxiao, 2012). Therefore, this paper selects the proportion of regional R&D expenditure to the total GDP to illustrate the impact of technological progress on carbon emissions.

c) Urbanization rate: With the development of economy, rural areas gradually transform into cities and towns, energy consumption and structure will change gradually. The area of farmland in the countryside has been greatly reduced. But at the same time, the development of urbanization is also an important prerequisite for the realization of a low-carbon living standard in rural areas. The wide application of low-carbon technology, clean energy and the change of people's lifestyle and life concept can help to reduce carbon emissions and achieve low-carbon, energy-saving and green development (Wang fang, zhou xing, 2012). Therefore, this paper selects the urbanization rate as a measure of the impact of urbanization on carbon emissions.

IV. Empirical Results Analysis

A. Stage 1: BCC Model Result Analysis

In the first stage, the traditional DEA model (BCC model) is used to analyze the original input-output data, and obtained the technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) of carbon emission reduction in various regions of China. From 2014 to 2016, the emission reduction efficiency values of 30 provinces and cities in China (except Tibet) were achieved by DEAP2.1 software. From 2014 to 2016, the average technical efficiency of initial emission reduction was 0.35. Only Beijing and Hainan province were at the forefront of effective technology, which technical efficiency was 1. While the other 28 provinces and cities are in the state of technical inefficiency. The average technical efficiency of Ningxia is the lowest, only 0.05. Therefore, the overall emission reduction efficiency of China's provinces and cities is low, and the regional differences are obvious.

B. Stage 2: Stochastic Frontier Model Result Analysis

Traditional BCC model cannot distinguish the influence factors of slack variables, and regarded that as internal management factors. Therefore, based on the analysis results of the first stage, this paper uses the stochastic frontier model (SFA) to analyze the carbon emission reduction efficiency after eliminating environmental factors, random variables and management inefficiencies. Since the non-expected output (carbon emission) is included in the DEA model as an input index in this paper, the redundancy results calculated in the first stage show that the total energy consumption redundancy of 30 provinces and cities in 2014-2016 is almost zero, which requires no further analysis. Therefore, this paper only takes the carbon emission input redundancy of 30 provinces and cities in China from 2014 to 2016 as the dependent variable, the proportion of the tertiary industry, the proportion of R&D expenditure and the urbanization rate as independent variables, and uses Frontier 4.1 software for regression analysis. The results are shown in “Table I”.

TABLE I. SFA Model Result

	Coefficient values	Standard deviation	T value
Constant term	13376.25	1.00	13375.93**
proportion of R&D expenditure	13922.16	1.00	-13922.14**
Urbanization rate	5327.55	1.00	5327.51**
proportion of the tertiary industry	14174.96	1.00	-14174.91**
Sigma-squared	51913713	1.00	51913713**
gama	0.98	0.003	309.54*
log likelihood function	-847		
LR test of the one-sided error	76.70*		

a. * and ** mean that T value is significant at 1% and 0.5% respectively.

As can be seen from “Table I”, all coefficient estimates have passed the T-value test, and the regression results are reliable. The regression results were tested by unilateral generalized likelihood ratio test. The gama value was nearly 1, which indicating that the influence of random variables on relaxation variables was almost zero, mainly due to external environmental factors and management inefficiency.

It can be seen from “Table I” that the proportion of R&D input is negatively correlated with the carbon emission slack (significance level of 0.5%). This suggests that investment in science and technology can reduce the slack in carbon dioxide emissions. Scientific and technological investment plays an important role in carbon dioxide emission reduction. Therefore, the relevant government departments should pay more attention to the allocation of funds on the basis of guaranteeing the investment of scientific research funds, so as to achieve higher carbon emission reduction efficiency. Secondly, there is a significant positive correlation between urbanization rate and carbon emission slack (0.5% significance level). According to the environmental Kuznets curve, the environmental quality will show an inverted U-shaped relationship with the economic development. The study of domestic scholar Wang fang et al. (2012) shows that the population urbanization rate and carbon emission also conform to the law of Kuznets curve, which means carbon emission will increase and then decrease with the increase of urbanization rate. From 2014 to 2016, China is still in the stage of further promoting urbanization, so the increase of urbanization rate will further promote the emission of carbon dioxide and reduce the carbon emission efficiency to a certain extent. Finally, there is a significant negative correlation between the proportion of the tertiary industry and the carbon emission slack (0.5% significance level). The increase of the proportion of tertiary industry reduces energy consumption and carbon emission. Therefore, adjusting the industrial structure and increasing the proportion of the tertiary industry will contribute to the improvement of carbon emission reduction efficiency in China.

C. Stage 3:Analysis of the Adjusted BCC Model

According to the adjusted input value, the BBC model is used again to evaluate the emission reduction efficiency of 30 provinces and cities. The efficiency value obtained in the third stage excludes the influence of environmental and random factors, and the results are more accurate to reflect the emission reduction level, as shown in “Table II”. The results of the third stage were implemented by DEAP2.1 software

Compared with the initial efficiency value, the adjusted emission reduction efficiency value changed obviously. The average comprehensive technical efficiency increased significantly from 0.350 to 0.407. The mean value of pure technical efficiency does not change much; the mean scale efficiency increased significantly from 0.594 to 0.708. Eliminating the influence of environmental and random factors, carbon emissions have changed under the condition of given output. Different regions are differently affected by external environmental factors, and the adjustment amount of carbon emissions is also different.

After the adjustment of input, the carbon emission reduction efficiency of Beijing and Hainan province is still 1, reaching the effective frontier of comprehensive technical efficiency. Guangdong, Shanghai, Jiangsu, Tianjin, Zhejiang and Fujian are the provinces and cities with an adjusted comprehensive technical efficiency of more than 0.50. These five provinces and cities are all located in the economically developed areas in the east. The provinces and cities whose comprehensive technical efficiency did not reach 0.20 were Gansu, Shanxi, Xinjiang and Ningxia. These four provinces and cities are all located in the economically underdeveloped areas in the west. 28 provinces and cities other than Beijing and Hainan, failed to achieve effectively technology efficiency. But their scale efficiency significantly increased after eliminating environmental and random factors, which shows that the gap between the actual scale efficiency and optimal scale efficiency is shrinking. However, the change of mean pure technical efficiency is not obvious, which indicates that while paying attention to the scale effect of emission reduction, advanced energy-saving and emission reduction technology should be gradually introduced, so as to achieve the dual effectiveness of scale and pure technical efficiency.

TABLE II. CARBON EMISSION REDUCTION EFFICIENCY VALUE

	2014			2015			2016		
Units	***TE***	***PTE***	***SE***	***PE***	***PTE***	***SE***	***PE***	***PTE***	***SE***
Beijing	1	1	1	1	1	1	1	1	1
Tianjin	0.555	0.632	0.878	0.544	0.620	0.878	0.549	0.603	0.878
Hebei	0.247	0.422	0.586	0.226	0.398	0.569	0.233	0.397	0.569
Shanxi	0.136	0.225	0.603	0.126	0.215	0.588	0.136	0.212	0.588
Neimenggu	0.22	0.370	0.612	0.203	0.342	0.594	0.194	0.303	0.594
Liaoning	0.334	0.542	0.616	0.306	0.510	0.599	0.224	0.356	0.599
Jilin	0.426	0.538	0.791	0.413	0.516	0.800	0.439	0.482	0.800
Heilongjiang	0.310	0.437	0.708	0.274	0.398	0.688	0.283	0.379	0.688
Shanghai	0.607	0.779	0.779	0.574	0.759	0.756	0.570	0.754	0.756
Jiangsu	0.568	0.964	0.589	0.551	0.956	0.577	0.567	0.970	0.577
Zhejiang	0.568	0.874	0.650	0.539	0.859	0.628	0.532	0.836	0.628
Anhui	0.441	0.639	0.690	0.420	0.622	0.676	0.451	0.610	0.676
Fujian	0.541	0.746	0.725	0.531	0.746	0.712	0.547	0.741	0.712
Jiangxi	0.514	0.632	0.813	0.475	0.599	0.793	0.516	0.595	0.793
Shandong	0.409	0.880	0.465	0.372	0.856	0.435	0.392	0.840	0.435
Henan	0.391	0.640	0.610	0.369	0.622	0.593	0.394	0.639	0.593
Hubei	0.443	0.664	0.667	0.433	0.668	0.649	0.444	0.665	0.649
Hunan	0.453	0.670	0.676	0.454	0.689	0.659	0.454	0.667	0.659
Guangdong	0.610	1.000	0.610	0.589	1.000	0.589	0.583	1.000	0.589
Guangxi	0.419	0.552	0.759	0.393	0.527	0.744	0.424	0.520	0.744
Hainan	1	1	1	1	1	1	1	1	1

	2014			2015			2016		
Units	**TE**	**PTE**	**SE**	**PE**	**PTE**	**SE**	**PE**	**PTE**	**SE**
Chongqing	0.451	0.538	0.838	0.447	0.547	0.817	0.467	0.550	0.817
Sichuan	0.367	0.570	0.644	0.358	0.569	0.630	0.364	0.572	0.630
Guizhou	0.215	0.292	0.735	0.211	0.293	0.721	0.243	0.303	0.721
Yunnan	0.293	0.397	0.737	0.292	0.398	0.733	0.311	0.394	0.733
Shanxi	0.398	0.577	0.690	0.341	0.510	0.669	0.367	0.491	0.669
Gansu	0.198	0.240	0.822	0.181	0.222	0.816	0.187	0.193	0.816
Qinghai	0.240	0.677	0.355	0.222	0.692	0.321	0.193	0.663	0.321
Ningxia	0.058	0.069	0.839	0.044	0.052	0.839	0.047	0.047	0.839
Xinjiang	0.130	0.199	0.655	0.116	0.182	0.635	0.108	0.159	0.635
Mean	0.418	0.592	0.705	0.4	0.579	0.69	0.405	0.565	0.731

V. Conclusions and Suggestions

A. Research Conclusions

Using the three-stage DEA model to evaluate carbon reduction efficiency of China's 30 provinces and cities from 2014 to 2016, this paper has the following conclusions:

- The carbon reduction efficiency of various provinces and cities in our country is generally low, but the annual average efficiency is on the rise, which suggesting that all regions have realized the importance of green development. Low carbon economy development is in good situation.
- There are obvious differences between regions in carbon emission reduction efficiency. According to the level of carbon emission reduction efficiency, 30 provinces and cities can be roughly divided into three regions: eastern economically developed regions, central regions and western economically underdeveloped regions. This shows that the level of economic development has an important impact on the carbon emission reduction efficiency of the region.
- After removing the influence of environmental factors such as industrial structure, technology R&D investment and urbanization degree in each region, the scale efficiency of carbon emission reduction is generally high, and the main reason for the low efficiency of carbon emission reduction is the low efficiency of pure technology, which indicates that the level of emission reduction technology is the key.

However, there are also some defects. First, taking carbon dioxide emissions as the input index causes the relaxation variable of energy consumption in the first stage BCC model was 0, so the relaxation was not regressive in the second stage. Second, the output index of carbon emission reduction efficiency is affected by a variety of factors. Due to the availability and comprehensiveness of data, this paper only picks the proportion of the tertiary industry, the proportion of R&D output and the urbanization rate as the environmental variables.

B. Policy Suggestions

From the enterprise level, enterprises are the main body to reduce carbon emission. First, enterprises should improve the awareness of energy conservation and emission reduction, take the initiative to introduce new technologies and eliminate the production lines with high pollution and low output. Secondly, enterprises should actively respond to government policies, such as incentive policies for active emission reduction and preferential policies based on annual emission reduction. Enterprises should real realize that emission reduction is not to achieve the government goals, but to make contributions to the sustainable development of themselves. Finally, enterprises should increase investment in scientific research and further study on waste gas recycling technology. Meanwhile, clean energy technology should be improved to reduce energy consumption.

From the government level, the government is an important guarantee to achieve energy conservation and emission reduction. First, government should accelerate industrial upgrading and adjust the energy consumption structure. Technological progress is the key to the development of China's low-carbon economy. On the one hand, technological progress can prompt enterprises to upgrade and transform from producing products with high pollution and high energy consumption to products with green environmental protection, so as to achieve simultaneous industrial development and emission reduction. At the same time, technological upgrading can have an impact on the energy consumption structure, which will change the extensive economic development model and achieve high-quality economic growth. Therefore, the central and western regions, in particular, should attach importance to investment in technological progress. Secondly, government should actively establish market-oriented emission reduction system and formulate various emission reduction policies. At present, the national carbon trading market is under construction. Before the official operation of the national carbon market, China's carbon trading pilot areas have achieved remarkable results in carbon emission reduction. Other non-pilot areas, under the pressure of low-carbon development, are fully aware that the use of market means is the key to achieve emission reduction and low-carbon development. The government should encourage enterprises to actively participate in carbon trading through various forms. Finally, the eastern, central and western regions should adopt different measures to gradually improve the efficiency of carbon emission reduction. The eastern region should give full use to its geographical advantages, and actively help the central and western regions achieve technological progress while acquiring the latest technologies to improve their own emission reduction efficiency. The central and western regions should constantly optimize and upgrade their industrial structure and gradually improve their carbon emission reduction efficiency with the support of national policies and the eastern regions.

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