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The Influence of Industrial Structure Upgrading on Carbon Emission Efficiency in China

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Abstract

Purpose - The industrial structure upgrading can play an important role in promoting the carbon emission efficiency. Thus, this paper attempts to study the impact of industrial structure upgrading on carbon emission efficiency in order to reduce carbon emissions.

Research design, data, and methodology - This paper selects panel data of 30 provinces and municipalities (autonomous regions) in China from 2001 to 2016, and divides them into three regions. The Moore index is used to measure the industrial structure upgrading, the non-radial SBM model based on undesired output is used to measure the slack variable to calculate the total factor carbon emission efficiency. Finally the impact of industrial structure upgrading on the carbon emission efficiency are analyzed.

Results - It is found that the Moore index and the carbon emission efficiency in the eastern region is the highest in the three regions.

Conclusions - The influence of various influencing factors on carbon emission efficiency is different between regions. The Moore index has a positive effect on the carbon emission efficiency in the eastern region, and has a negative influence coefficient on the central region. The effect on the western region is not obvious.

Keywords: Industrial structure upgrading, Moore index, SBM model, carbon emission efficiency.

JEL Classification: L50, O13, R11

1. Introduction

China's economy has developed rapidly since the 21st century. At the beginning of the century, China has held its own place in the world economy by virtue of its resource-intensive and labor-intensive industries. However, it is the huge energy consumption and pollutant emissions behind the fast-growing economy. Since 2006, China has become the world's largest carbon emitter and has been the world's largest energy consumer since 2009. Although China's carbon dioxide emissions have declined after a series of efforts, China's emissions reduction pressure is still very large. Reducing the carbon dioxide emissions by comprehensively improving the total factor carbon dioxide emission efficiency has a major impact on the quality of China's economic growth and the external environment. Industrial restructure upgrading has become a core tool for coordinating the economy and the environment. Therefore, under the existing technology level, how to adjust the industrial structure to control China's energy intensity and carbon intensity has been widely concerned by government departments and researchers. The industrial restructure upgrading based on energy conservation and emissions reduction is also consistent with the economic with low-carbon development behavior advocated by the Chinese government in the 13th Five-Year Plan.

Through the analysis of relevant literature, the previous literature about the industrial structure has been more mature. Therefore, it can be seen from the previous research literature that the study of industrial structure upgrading and its impact on carbon emission efficiency is very reasonable, it is significant for the realization of China's energy saving goal. However, the indicators used in the past literature to measure the upgrading of industrial structure

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have certain limitations, which can only reflect whether the industrial structure upgraded or not, and cannot reflect the direction of industrial structure upgrading. This paper uses the Moore index to overcome this shortcoming and the non-radial SBM model based on undesired output is used to calculate the slack variable and GML index, then the total factor carbon emission efficiency under multi-input and multi-output is calculated according to the slack variable, and finally the impact of industrial structure upgrading on carbon emission efficiency is analyzed.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the methodology. Section 4 analyzes the empirical results and discussion in China and in the three major economic regions of China. Section 5 consists of conclusions and recommendations.

2. Literature Review

First, some researchers studied the impact of industrial structure on carbon emission. Kaya and Yokobori (1993) first proposed the concept of carbon productivity and defined carbon productivity as the ratio of carbon dioxide emissions to nominal GDP. According to optimistic estimates by scholars, industrial restructure change has contributed more than 70% to achieving carbon intensity target (Wang, 2014). Zhang (2014) measured the optimal industrial adjustment path for China to achieve the minimum fluctuation of the national economy, and revealed the key industries that should encourage and control development under the low-carbon economy and sustainable development, and believed that with the tightening of carbon emission reduction constraints and the improvement of economic growth targets, the required industrial structure adjustment will gradually increase, and the structural changes required for strengthening emission reductions will be greater than the changes required for higher economic growth rates. Wu, Huang, and Chuai (2015) used the EIO-LCA method to analyze the hidden carbon of various industrial sectors in Jiangsu Province from production to supply chain to consumption, and on this basis, explored the carbon emission reduction potential of industrial restructure adjustment and provided a theoretical reference for the scientific formulation of emission reduction policies in Jiangsu Province. Zhang, Liao, and Yang (2017) constructed the industry's energy structure consumption matrix and carbon row structure matrix through the industry's production structure matrix, aiming to get the optimal industrial structure adjustment plan of China in 2020 under the dual constraints of energy consumption and carbon dioxide emissions, and calculated the potential of China's largest carbon emissions based on the existing technology level. Diana (2018) introduces the Markov conversion mechanism into the productivity framework to measure how sustainable development and corporate restructuring occur in the face of industrial transformation and structural change, and analyzed the impact of dynamics and structural changes of industrial development on sustainable development, and believed that the industry should adopt sustainable economic policies based on environmental impacts. Zhang, Jiang, and Liu (2018) used a dynamic factor model to decompose and compare the impact of industrial structure on carbon emission reduction, studied the industrial structure in China during the five-year plan period from 2006 to 2030 from the perspective of industry and sector and the result showed that China's industrial structure had a positive impact on carbon emission reduction potential and this effect varied with the proportion of sectors in the economic structure.

Second, some literature studied the related problems about carbon emission efficiency. Chang, Zhang, and Chang (2016) verified that the allocation standard based on Shapley value is an equal and effective allocation of emission reduction targets. Zhang (2017) uses the systematic general method of moments to estimate the impact of environmental innovation on carbon emissions. Labor mobility between the first, second and tertiary industries helps to increase TFCE (TFP adjusted by energy consumption and carbon dioxide emissions), carbon efficiency and energy consumption efficiency, but capital transfer does not produce the same effect (Li & Lin, 2017). Zhang et al. (2018) used DEA-based Meta-frontier non-radial DDF to measure carbon emissions performance and found that the CDM project does not necessarily contribute to improving carbon emissions performance in most countries. Román and Morales (2018) found that the main drivers of increased carbon dioxide emissions include population intensity, human activities, carbonization processes and fossil fuel combustion. Iftikhar, Wang, and Zhang (2018) found that economic and distribution inefficiencies affect CO_2 emissions efficiency. Bye, Fæhn, and Rosnes (2018) focused on Norway's 2030 residential energy efficiency policy objectives and explored their interactions with carbon dioxide emission targets.

3. Methodology

3.1. Measurement Method of Industrial Structure Upgrading

Although the previous research on industrial structure adjustment can reflect the law of industrial structure change in general, it only focuses on the static description of industrial structure in the current period, which does not reflect the degree of inter-temporal change of industrial structure. As pointed out by Zhang and Pu (2015), the traditional service index ignores the evolutionary characteristics of the primary industry. Therefore, it is

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necessary to make a more detailed division of the industrial structure, and pay attention to dynamic changes in the index construction that represents the adjustment of industrial structure in order to reflect the extent and direction of the industrial structure's inter-temporal changes. According to Zhou and Ren (2011), this paper divides the macroeconomic industrial structure into seven major industries. The order of the industrial grades from low to high is: agriculture, industry, construction, real estate, wholesale and retail accommodation and catering, Transportation Warehousing postal industry and the financial industry to form regional industrial structure vectors, and then calculate the degree of change in each industry separately. When calculating the Moore value of the j industry in i region, it is assumed that the proportion of other industries in the t+1 period is the same as that in the t-th period, and the Moore value of the j industry from the t-th period to the t+1-th period is calculated. It is assumed that the proportion of other industries other than the j industry in the t-th region of the i region is the same as that in the t+1 period, and the Moore value of the j industry from the t-th phase to the t+1-th period is calculated. Then, the geometric mean of the Moore value is taken twice as the transition degree of the j industry in the i region from the t-th to the t+1-th. Finally, the Moore values of all industries are aggregated, and the j industry arranged in the j position is repeatedly superimposed j times to indicate the direction of industrial structure change. However, this practice still ignores the importance of the j industry in the economic development of the region. Therefore, this paper follows the calculation method of Zhang and Pu (2015), and adds the proportion of the output value of the j industry when calculating the Moore value of the i region.

First, calculate the $Moore_{i,t+1}^{i,j}$ of the j industry in the i region from the t-th to the t+1-th.

$$Moore_{i,t+1}^{i,j} = \sqrt{\left[\frac{\sum_{k\neq j}\left(p_{i,t}^{k}\right)^2 + p_{i,t}^{j} * p_{i,t+1}^{j}}{\sqrt{\sum_{k=1}^{m}\left(p_{i,t}^{k}\right)^2 * \left[\sum_{k\neq j}\left(p_{i,t}^{k}\right)^2 + \left(p_{i,t+1}^{j}\right)^2\right]}}\right] * \left[\frac{\sum_{k\neq j}\left(p_{i,t+1}^{k}\right)^2 + p_{i,t}^{j} * p_{i,t+1}^{j}}{\sqrt{\sum_{k=1}^{m}\left(p_{i,t+1}^{k}\right)^2 * \left[\sum_{k\neq j}\left(p_{i,t+1}^{k}\right)^2 + \left(p_{i,t}^{j}\right)^2\right]}}\right]} \quad (1)$$

Then, the degree of industrial structure upgrading between the t-th and t+1th periods in the i region is as follows:

$$Moore_{i,t+1}^{i} = \sum_{j=1}^{m}\left[j * p_{i,t}^{j} * Moore_{i,t+1}^{i,j}\right] \quad (2)$$

3.2. Analysis of the Calculation Results of Industrial Structure Upgrading

In order to analyze regional differences, according to Zheng and Yang (2017), 30 provinces (autonomous regions) are divided into three main economic regions: the eastern region, the central region, and the western region. The eastern region includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan. The central region includes includes 8 provinces: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. The western region includes 11 provinces: Chongqing, Sichuan and Guizhou. Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi and Inner Mongolia. The specific division is shown in Table 1.

Table 1: Three economic regions

Regions	Provinces
East	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan
Central	Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan
West	Chongqing, Sichuan , Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi, Inner Mongolia

Note: Due to the lack of data, Tibet, Hong Kong, Macao, Taiwan are not included in this paper.

According to equation (1) and equation (2), this paper measures the Moore values of the three regions from 2001 to 2016. Table 2 shows the industrial structure change values of the three regions. It can be seen that the inter-temporal changes of industrial structure have regional differences. From the average of Moore value, the speed of industrial structure upgrading in the eastern region is the fastest. The average speed of industrial structure changes in the 11 provinces and autonomous regions in the western region is second, and the average speed in the 8 provinces in the central region is the slowest. This is mainly because the role of further changes in the industrial structure reflected in each region is different. In recent years, the implementation of national policies has also had a significant impact on the three major regions. The open economy in the eastern region has developed rapidly under the promotion of policies, the technical level has been significantly improved, and industrial structure has been promoted. The implementation of the western development policy, especially the implementation of the new "Silk Road", the western region has been influenced by the international and domestic markets, which has greatly boosted the western region development. Due to its inland location, the central region is subject to certain restrictions, the industrial structure changes and upgrades are the slowest.

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Table 2: Moore value in three regions

	East	Central	West	Average
2001	2.592 3	2.419 0	2.404 2	2.477 1
2002	2.571 6	2.449 2	2.406 3	2.478 3
2003	2.541 4	2.433 6	2.410 1	2.464 5
2004	2.518 1	2.412 7	2.389 8	2.442 9
2005	2.364 6	2.290 4	2.244 6	2.300 8
2006	2.478 2	2.292 7	2.342 3	2.378 9
2007	2.498 7	2.314 2	2.352 2	2.395 8
2008	2.528 5	2.318 2	2.341 7	2.403 9
2009	2.524 9	2.308 2	2.330 0	2.395 7
2010	2.632 5	2.355 4	2.428 2	2.483 7
2011	2.657 5	2.358 7	2.430 4	2.494 6
2012	2.654 9	2.337 9	2.434 5	2.489 5
2013	2.671 1	2.365 5	2.467 4	2.514 9
2014	2.683 5	2.415 8	2.492 0	2.541 9
2015	2.693 0	2.559 4	2.559 5	2.555 6
2016	2.679 7	2.523 0	2.490 6	2.474 6
Mean	2.580 7	2.365 1	2.396 9	2.455 8

Figure 1 shows the time trends of industrial structure upgrading in the three regions. It can be seen that: (1) from the comparison of the degree of industrial structure upgrading, compared with other regions and the national average, the Moore value in the eastern region is the highest, higher than the national average and the central region and the western region. The level of structural change upgrading is higher in the western region than that in the central region and below the national average. This result is consistent with the economic development level and policy implementation of the three regions. (2) From the perspective of the time trends of the industrial structure upgrading, the degree of industrial structure change in the three major regions has stage volatility with time. This result is the same as the national analysis results. The fluctuations are divided into three stages: the first stage is 2001-2005, the industrial structure upgrading in the eastern, central and western regions are slow. The trend is because this stage has just entered the 21st century, and the level of economic development is relatively backward. The industrial structure in regions mainly include resource-intensive and labor-intensive industries, and the industrial structure upgrading rate is slow or even declining; the second stage is 2006-2010, the rate of industrial structure upgrading at this stage has increased compared with the previous stage. The proportion of low-end industries has been decreasing, high-end industries have been developed, and industrial structure has been upgraded; the third stage is 2011-2016, in the early stage, the industrial structure upgrading rate is fast. This is because the rapid development of new technology in recent years has greatly improved the technical level. Later in this stage, as the industrial structure upgraded to a certain extent, the resistance became larger and the upgrading speed slowed down.

3.3. Measurement of Carbon Emission Efficiency

In this paper, the non-radial non-angled SBM model based on slack variables proposed by Tone (2001) is used to introduce carbon dioxide emissions as undesired outputs into the SBM model to measure the total factor carbon emission efficiency in order to avoid radial and angular the interference caused by the measurement results. The specific method is as follows: this paper supposes that K represents the number of DMUs (k=1, 2...K), that T represents the production time (t=1, 2...T), and that any DMU can use N kinds of input to gain M kinds of desired output and B kinds of undesired output. And the production possibilities set can be defined as $P(x)=\{(y,b)|x \; can \; \text{produce}(y,b)\}$. Generally, input factors and desired outputs satisfy strong disposition, and undesired outputs satisfy weak disposition.

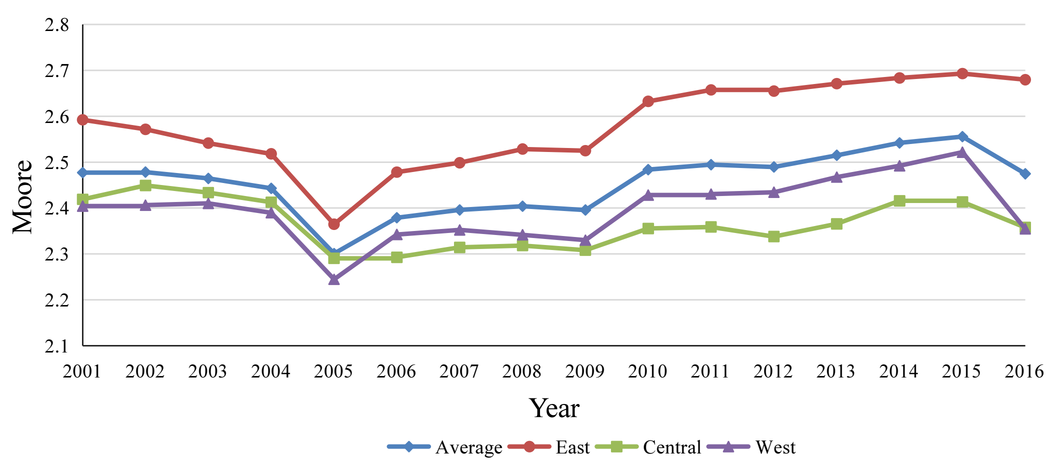

Figure 1: Time trends of industrial structure upgrading in the three regions

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Based on the above basic assumptions, this paper sets the non-radial SBM model considering the undesired output as follows:

$$\theta = \min \frac{1-\frac{1}{N}\sum_{n=1}^{N}\frac{s_{kn}^{x}}{x_{kn}}}{1+\frac{1}{M+L}\left(\sum_{m=1}^{M}\frac{s_{km}^{y}}{y_{km}}+\sum_{l=1}^{L}\frac{s_{kl}^{b}}{b_{kl}}\right)} \quad (3)$$

s.t. $\sum_{k=1}^{K}\lambda x_{kn} + s_{kn}^{x} = x_{kn}, \forall n$ (4)

$$\sum_{k=1}^{K}\lambda_k y_{km} - s_{km}^{y} = y_{km}, \forall m \quad (5)$$

$$\sum_{k=1}^{K}\lambda_k b_{kl} + s_{kl}^{b} = b_{kl}, \forall l \quad (6)$$

$$\lambda_k \geq 0, \forall k \quad (7)$$

$$s_{kn}^{x} \geq 0, s_{km}^{y} \geq 0, s_{kl}^{b} \geq 0 \quad (8)$$

$$\sum_{k=1}^{K}\lambda_k = 1 \quad (9)$$

Where x_{kn}, y_{km} and b_{kl} represent the nth input, the mth expected output, and the lth undesired output of the kth decision unit, respectively, and s_{kn}^{x}, s_{km}^{y} and s_{kl}^{b} represent inputs, undesired outputs and the slack variable, respectively.

The slack variable in equation (3) is a direct quantification of inefficiency, that is the difference between the corresponding actual input and output and the corresponding input and output under full efficiency. Based on the above ideas, this paper defines the total factor carbon emission efficiency (TFCE) as the carbon dioxide emission efficiency under multiple inputs and multiple outputs as the total factor carbon emission efficiency, which specifically refers to the ratio of the target carbon dioxide emissions to the actual carbon dioxide emissions under the full efficiency. It can be specifically defined as follows:

$$TFCE = \frac{actual\ output(CO_2) - slack(CO_2)}{actual\ output(CO_2)} = \frac{target\ output(CO_2)}{actual\ output(CO_2)} \quad (10)$$

The TFCE in equation (10) considers the total factor efficiency under the combined action of capital (K), labor (L) and energy (E). It mainly reflects two meaning: first, it explains the impact extent of factor endowment to carbon dioxide emissions; second, it portrays the environmental costs of economic growth.

3.4. The Calculation Results of Carbon Emission Efficiency

This paper takes labor, capital, energy consumption as input, GDP as desired output, carbon dioxide emissions as undesired output, and adopts non-radial SBM model based on undesired output. The slack variable is measured by MaxDEA software and the total factor carbon emissions efficiency is calculated by equation (10). Figure 2 shows the time trends of carbon emission efficiency in the three regions. From the regional perspective, the carbon emission efficiency in the eastern region has been at a high level and is the highest in the three regions. The carbon emission efficiency level in the western region is the lowest and the overall efficiency level is relatively stable. The carbon emission efficiency level in the central region is between the eastern and western regions, and shows an upward trend. This is because the provinces in eastern region are mostly coastal developed areas with the most convenient transportation conditions and the earliest implementation of reform and opening up. The central and western regions are in China's inland areas. The traffic conditions and historical factors have led to an underdeveloped economic level and the technical level.

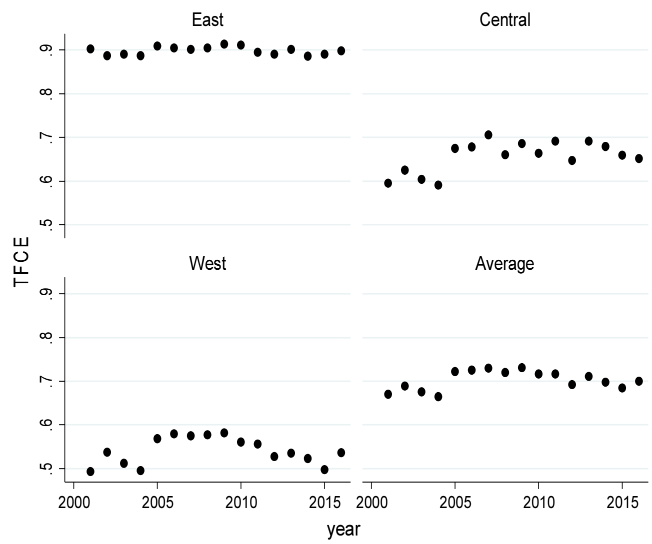

Figure 2: Time scatter plot of carbon emission efficiency in the three regions.

4. Empirical Analysis

4.1. Model Establishment and Tests

The purpose of this paper is to study the impact of industrial structure upgrading and technological progress on carbon emission reduction potential. Moore index is as a core explanatory variable, energy consumption structure (ES), environmental regulation (ER), foreign direct investment (FDI) and R&D investment (RD) are added as control variables to construct the measurement model of the factors that influence the total factor carbon emission efficiency as shown in equation (11) .

$$TFCE = \beta_0 + \beta_1 Moore + \beta_2 ES + \beta_3 ER + \beta_4 FDI + \beta_5 RD + \mu \quad (11)$$

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4.1.1. Multi-collinearity Test

In the existing literature, the correlation coefficient matrix between variables is used as as evaluation criterion to test the multi-collinearity. One drawback of the above approach is that even if the correlation coefficient between variables is small, the model may still have the possibility of multicollinearity due to the interaction between variables. In order to overcome this limitation, the variance inflation factor is used to test whether there is a multi-collinearity between variables or not. The calculation results of the variance inflation factor are shown in Table 3. According to the judgment experience, the criterion for judging the multi-collinearity must be satisfied at the same time: (1) the maximum VIF is greater than 10; (2) the average VIF is greater than 1. It can be seen from the results in Table 3 that the maximum value of VIF is only 1.36, which is much less than 10, which does not meet the first criterion of the criterion for variance expansion factor. The multi-collinearity problem of the model does not cause a large bias to the estimation results, and can be ignored (Yao, Yang, & Gao, 2016).

Table 3: Calculation results of variance inflation factor

Variable	VIF	1/VIF
Moore	1.33	0.753 829
GPC	1.03	0.968 033
GDP	1.14	0.875 183
ES	1.34	0.747 889
ER	1.26	0.796 199
FDI	1.36	0.733 639
Mean VIF	1.24	

4.1.2. Heteroscedasticity and Autocorrelation Tests

If the model has heteroscedasticity, then if the ordinary least squares estimation is used, although the parameter estimator still satisfies linearity and unbiased conditions but it will make the parameter estimator lose its validity, the significance test of the variables loses its meaning, and the model is used for prediction is invalid. The existence of autocorrelation will also make the estimation result ineffective. Considering these problems, this paper uses the modified Wald test, the Woodridge test and the Friedman test to test the heteroscedasticity, first-order autocorrelation and contemporaneous correlation between the groups. The results of heteroscedasticity and autocorrelation tests are shown in Table 4. It can be seen from the results in Table 4 that there is no heteroscedasticity in the model, but there is a first-order autocorrelation and a contemporaneous correlation between the groups. Therefore, considering these problems, this paper uses the comprehensive feasible generalized least squares (FGLS) to solve this problem (Chen, 2014).

Table 4: Heteroscedasticity and autocorrelation tests

Tests	Null hypothesis	Statistics	P-value
Modified Wald test	Same variance	5.24	0.994 4
Woodridge test	No first-order autocorrelation	181.833	0.000 0
Friedman test	No contemporaneous correlation between groups	2231.630	0.000 0

4.2. Data Sources and Indicators

This paper selects the panel data of 30 provinces (autonomous regions) in China from 2001 to 2016. This paper studies the total factor carbon emission efficiency, thus input factors include labor, capital and energy consumption, desired output factors is GDP and undesired output is carbon dioxide emissions. In particular, the calculation of capital stock draws on the method of Shan (2008), and the calculation of carbon dioxide emissions refers to the calculation methods of carbon dioxide emissions of standard coal by Tu and Liu (2014). The calculation of industrial structure upgrading refers to the practice of Wu, Wang, and He (2018) and uses the Moore index. The level of economic development is expressed by GDP. The energy consumption structure is expressed by the proportion of coal consumption in total energy consumption. The environmental regulation uses the proportion of the environmental pollution control investment in GDP. Foreign direct investment uses the actual use of foreign direct investment in GDP. The original data come from the 2002-2017 China Statistical Yearbook, China Energy Statistical Yearbook and the Provincial Statistical Yearbooks.

4.3. Discussions about Empirical Results

4.3.1. National Empirical Results

This paper analyzes the factors affecting the carbon emission efficiency of 30 provinces and municipalities (autonomous regions) in China. The empirical results are shown in Table 5. This paper uses the method of gradually adding control variables. The results show that the Moore value has a significant positive impact on carbon emission efficiency, which indicates that the industrial structure upgrading will significantly improve the total factor carbon emission efficiency. Among the control variables, the impact of GDP on carbon emission efficiency is positive. As the level of economic development increases, technology level will improve, which will help improve carbon emission efficiency. There is a significant negative correlation between energy consumption structure and carbon emission efficiency which indicates that reducing coal consumption will help improve carbon emission efficiency. The impact of environmental regulation on carbon emission efficiency is significantly negative. One possible explanation is that this paper uses the proportion of environmental pollution control investment in GDP to represent environmental regulation. In

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fact, the total investment in environmental pollution control is increasing year by year. However, the growth of GDP exceeds the growth of investment, which leads to a decrease in the proportion of each year. Therefore, the coefficient of environmental regulation is negative. The impact coefficient of FDI on carbon emission efficiency is significantly positive, indicating that foreign direct investment has a technology spillover effect, which will help improve carbon emission efficiency.

4.3.2. Empirical Results in the Three Regions

Table 6 shows the empirical results of the factors affecting carbon emission efficiency in the three regions. In the eastern region, the results show that the impact coefficient of Moore index on carbon emission efficiency is significantly positive, indicating that the industrial structure upgrading will promote the improvement of carbon emission efficiency. There is a negative correlation between energy consumption structure and carbon emission efficiency. Reducing the proportion of coal consumption in total energy consumption will promote the carbon emission efficiency. FDI has a significant positive impact on carbon emission efficiency, which is consistent with the country. In the central region, the impact coefficient of the Moore index on carbon emission efficiency is significantly negative, and the impact of foreign direct investment on carbon emission efficiency is significantly positive. In the western region, the industrial structure upgrading has a significant positive impact on carbon emission efficiency, and the coefficient of GDP is significantly positive, which is similar to the national results. The impact coefficient of the energy consumption structure is significantly negative, and the reduction in the proportion of coal consumption will also help improve the carbon emission efficiency. The impact of environmental regulation on carbon emission efficiency is negative.

Table 5: Empirical results of factors affecting carbon emission efficiency in China

	(1)	(2)	(3)	(4)	(5)
Variables	TFCE	TFCE	TFCE	TFCE	TFCE
Moore	0.157 0***	0.127 0***	0.095 2***	0.107 0***	0.031 3***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP		0.011 4	0.011 5	0.007 6	0.014 8*
		(0.054)	(0.080)	(0.320)	(0.013)
ES			-0.209 0***	-0.175 0***	-0.104 0***
			(0.000)	(0.000)	(0.000)
ER				-0.021 9***	-0.023 8***
				(0.000)	(0.000)
FDI					0.023 6***
					(0.000)
_cons	0.418 0***	0.415 0***	0.557 0***	0.489 0***	0.466 0***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	480	480	480	480	480

Note: ***, **, * indicate that the coefficients are significant at the statistical levels of 1%, 5% and 10%, and the value p statistics is in parentheses.

Table 6: Empirical results of factors affecting carbon emission efficiency in three regions

Regions	East		Central		West	
Variables	TFCE	TFCE	TFCE	TFCE	TFCE	TFCE
Moore	0.124 0***	0.018 2***	-0.481 0***	-0.476 0***	0.301 0***	0.017 5***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP		-0.002 9		-0.014 0		0.102 0***
		(0.592)		(0.426)		(0.000)
ES		-0.288 0***		-0.076 0		-0.032 8*
		(0.000)		(0.113)		(0.044)
ER		-0.003 5		0.010 0		-0.093 4***
		(0.421)		(0.581)		(0.000)
FDI		0.026 3***		0.059 7***		0.004 3
		(0.000)		(0.000)		(0.353)
_cons	-0.144 0***	0.379 0***	1.364 0***	1.284 0***	1.083 0***	0.821 0***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	176	176	128	128	176	176

Note: ***, **, * indicate that the coefficients are significant at the statistical levels of 1%, 5% and 10%, and the value p statistics is in parentheses.

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5. Conclusions and Recommendations

This paper selects the panel data of 30 provinces (autonomous regions) in China from 2001 to 2016, and divides them into three regions to study the impact of industrial structure upgrading on carbon emission efficiency. The results show that the degree of industrial structure upgrading over time is different between provinces and regions, with the features of overall stability, stage volatility and regional differences. The Moore value in the eastern region is the highest, higher than the national average and the central and western regions. The Moore index has a positive effect on carbon emission efficiency in the eastern and western regions, and has a negative impact coefficient on the central region. The improvement of the level of economic development has a positive effect on the carbon emission efficiency in the western region. The energy consumption structure has a negative impact on carbon emission efficiency in the eastern and western regions, meaning that reducing the share of coal consumption in energy consumption can help improve carbon efficiency. Foreign direct investment has a positive effect on the eastern and central regions, which can effectively promote the carbon emission efficiency. Based on the empirical results, this paper proposes the following policy recommendations.

(1) Improve the carbon emission reduction effect of the industrial structure. The government should encourage resource-intensive industries to transform into capital-intensive and technology-intensive industries, accelerate the transformation and upgrading of traditional resource-based industries, and promote the rapid development of emerging industries. The government should formulate relevant policies to promote industrial upgrading, focus on controlling and rectifying traditional industries with excessive carbon emissions, and promote the transformation and upgrading of resource-oriented industries to high-efficiency and low-carbon industries.

(2) Pay attention to the effect of other influencing factors on carbon emission efficiency. All regions should reduce the proportion of coal consumption in energy consumption and improve the development level of clean energy and continue to increase investment in environmental pollution control, set the threshold for foreign direct investment, and attract high-quality investment.

(3) Encourage inter-regional collaboration to improve carbon emission efficiency. Strengthen cooperation exchanges between regions, and the government can establish a joint governance system with neighboring regions to reduce the impact of external carbon emissions on the region through collaboration between the region and neighboring regions. Each region can exchange and learn advanced emission reduction technologies to improve their carbon emission reduction capacity so as to achieve carbon emission reduction targets at an early date.

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