

Retraction

Retracted: Regional Variation in the Carbon Dioxide Emission Efficiency of Construction Industry in China: Based on the Three-Stage DEA Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] W. Zhou and W. Yu, "Regional Variation in the Carbon Dioxide Emission Efficiency of Construction Industry in China: Based on the Three-Stage DEA Model," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 4021947, 13 pages, 2021.

Research Article

Regional Variation in the Carbon Dioxide Emission Efficiency of Construction Industry in China: Based on the Three-Stage DEA Model

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China's construction industry emits a huge amount of carbon dioxide with the extensive and rapid development, and the carbon dioxide emissions from construction sector have become a social problem. This article evaluates the carbon dioxide emission from China's regional construction industry by the three-stage DEA method. The research results indicate that the environmental factors and random error seriously affect the carbon dioxide emission efficiency of construction industry. Eliminated the above factors, the mean of the carbon dioxide emission efficiency has the tendency of rising firstly and then decreasing, which increased from 0.67 in 2010 to 0.76 in 2014 and then decreased to 0.66 in 2019 in the third stage. On the whole, China's regional construction industry has the low carbon dioxide emission efficiency. In the regions, the Eastern region has the highest technology efficiency value among the three regions, followed by the Middle region and the West region. Therefore, the key method to increase the carbon emission efficiency of construction industry is to improve the management efficiency and change the growth mode.

1. Introduction

The construction industry of China has a dramatic improvement in recent years. The gross annual value of construction industry has increased from 138.2 hundred million Yuan in 1978 to 248443 hundred million Yuan in 2019. There are 54 million workers employed in construction industry, accounting for 6.69% of the total employed in China [1]. The construction industry also drives the development of related industries. For example, steel industry, cement industry, and construction equipment industry. There is no doubt that the construction industry has become a pillar sector in China. The goal of the Industrialization and Urbanization was put forward in the 14th Five-Year-Plan (14th FYP, corresponding the years of 2021–2025), which is issued by the government. New urbanization will provide great opportunities for the construction industry. Firstly, the new urbanization will create huge investment demand for

the construction industry. During the 14th Five-Year-Plan period, a large number of migrant workers will swarm into cities, which will drive a huge investment demand for housing and infrastructure. Secondly, the new urbanization can also promote the development of green buildings. The new cities are characterized by intelligence, low-carbon, and environmental friendliness. The construction industry must meet the requirements of new urbanization by applying green materials, new technologies, and energy-saving equipment. Thirdly, the industrialized construction mode, such as prefabrication, BIM, and intelligent construction, will meet the new opportunity. Therefore, China's construction industry will come upon an important strategic opportunity in 2021–2025.

On the other hand, the carbon dioxide emissions from China had increased 2777 million tons in 2019, which accounts for 28.8 percent of global carbon dioxide emissions and exceeded the total amount sum emissions from the

United States, India, Russia, and Japan [2]. A large number of carbon dioxide emissions created serious environmental problems [3], such as the greenhouse effect, abnormal climate, and the flood disasters, which seriously threatened the survival of mankind. In order to cope with the increasing environmental disaster, the government of China presented the goal to achieve carbon emissions peak by 2030 and become carbon neutrality by 2060 [4], which illustrated the general requirements for energy saving and low-carbon development.

The carbon dioxide emissions from China's construction industry have increased from 16821 thousand tons standard coal in 2010 to 21432 thousand tons standard coal in 2019, which accounts for half of the China's carbon dioxide emissions. Undoubtedly, improving of carbon dioxide emission efficiency in construction industry is the key factor to achieve the energy-saving and low-carbon development goals.

This article is organized as follows: Section 2 sorts out the relevant theories on the carbon dioxide emissions. Section 3 introduces two research methods and establishes the three-staged DEA model to calculate the emissions of carbon dioxide in construction industry. Section 4 gets the research results and discusses the carbon dioxide emission efficiency from construction industry. Section 5 draws the conclusions and gives the advice to improve the carbon dioxide emission efficiency from China's construction industry.

2. Theory

2.1. The Definition of Carbon Dioxide Emission Efficiency. The studies on carbon dioxide emission efficiency in different industries have been a hot field. But so far, scholars have not getting a unified definition on carbon dioxide emission efficiency. At present, the carbon dioxide emission efficiency is mainly defined from two perspectives: (1) it is defined as the ratio of two variables from the perspective of single factor. Scholars often use carbon emission intensity, carbon dioxide emissions index, or carbon productivity to characterize the carbon emission efficiency. Here, the carbon dioxide emission intensity is the ratio of carbon dioxide emissions to the per unit of GDP, some scholars insisted that it is an ideal indicator to calculate the carbon dioxide emission efficiency [5, 6]. Carbon dioxide emissions index refers to the carbon dioxide emissions per unit of energy consumption [7]. The carbon productivity referred the ratio of GDP to carbon dioxide emissions [8, 9]. (2) The carbon dioxide emission efficiency can be defined as the total factor productivity from the perspective of multifactors. Many scholars thought that the carbon index theory or carbon dioxide emissions intensity theory had faults because carbon dioxide emission efficiency should not only be measured in a single respect. Therefore, scholars began to research the carbon emission efficiency from the perspective of total factor productivity [10–12]. They used multi-input variables and multioutputs variables to measure the carbon dioxide emission efficiency and insisted that the evaluation of carbon emission efficiency was more comprehensive and reasonable only by integrating the carbon dioxide emissions into the

whole economic system. Furthermore, scholars took carbon dioxide emissions as undesirable (bad) output in the production process and put forward the comprehensive evaluation index of carbon dioxide emissions [13, 14].

2.2. Influencing Factors on Carbon Dioxide Emission Efficiency. Almost scholars take the population and per income as the main factors influencing carbon dioxide emissions [15–17]. Besides, many scholars deemed that energy structure, urbanization, industry type, and carbon emissions of per unit energy consumption are major factors affecting carbon dioxide emission efficiency [18, 19]. While, Feng et al. [20] and Lu et al. [21] believed that the building materials and building equipment are major factors to affect carbon dioxide emissions of China's construction industry.

2.3. The Research Methods for Carbon Dioxide Emission Efficiency. There are two main methods to research the carbon dioxide emission efficiency: one is Parametric Methods and another is Nonparametric Methods.

Firstly, the Parametric Method is presented by stochastic frontier analysis (SFA) [22]. Many scholars used the SFA method to research the carbon dioxide emission efficiency from the country or district view. Such as, Herrala and Goel [23] measured the global carbon dioxide emission efficiency. Liu et al. [24] calculated productivity of road transportation industry, which indicated that technological and scale efficiency promote the productivity growth. Zhang and Zhong [25] estimated the carbon dioxide emission efficiency of China from the regions view by the SFA method, which showed that carbon dioxide emission efficiency is low and the gap between regions is obvious. From the construction industry view, Boyd and Lee [26] used SFA method to calculate the fuel energy efficiency in five manufacturing industries in the United States. Liu et al. [27] measured the convergence of the production efficiency in region's construction industry. Nazarko and Chodakowska [28] estimated the labor efficiency of Europe's construction industry by SFA model.

The dominant method to estimate the carbon dioxide emission efficiency at present, the Nonparametric Method, is the Data Envelopment Analysis (DEA). Farrell [29] created firstly the nonparametric method to calculate the technology efficiency. Charnes et al. [30] proposed DEA-CCR model based on Farrell's method. After that, Banker et al. [31] built the DEA-BCC model. Kiril et al. [32] calculated the energy efficiency by the DEA model employing the labor and capital as key variables and found that energy efficiency does not increase. Wang et al. [33] collected the data to estimate the difference of environmental efficiency in top 20 Asian economies, the results indicated that Japan did the best in energy efficiency than others and was a good example to protect environment. Wei et al. [34] analyzed the effecting factors of carbon dioxide emissions and estimated China's carbon dioxide emission efficiency by the DEA method using the panel data from 1986 to 2008. The results showed that industrial structure and openness are negatively related to carbon emission efficiency, whereas public investment and energy price are positively related to carbon emission efficiency.

Comparing with the SFA method, the DEA method has many advantages, such as it does not need to model the specific form, is not affected by the dimension, and can deal with the problem of multi-input and multioutput. Therefore, DEA method is more suitable to research carbon emission efficiency. But the weakness of the DEA model is that it cannot rule out the affecting of environmental factors and random error on Decision-Making Units (DMUs) efficiency. In order to overcome the default of the DEA model, Fried et al. [35] created three-stage DEA model to calculate the relative efficiency of different DMUs. Now, the three-stage DEA model is used widely to estimate efficiency in different fields.

Through sorting out the relevant literature, we find that the related researches do not rule out the influence of environmental factors and random errors on carbon dioxide emission efficiency and cannot reflect the real carbon dioxide emission efficiency of construction industry. For overcoming the weakness of traditional DEA model, this article takes the three-stage DEA model to calculate carbon dioxide emissions of construction industry in China and hope to obtain the more accurate carbon dioxide emission efficiency.

3. Methods

The three-stage DEA model combines the advantages of the DEA model and the SFA model, which is composed by the following three stages.

3.1. The First Stage: Traditional DEA Model to Analyze Initial Efficiency. Charnes et al. [30] created DEA-CCR model in 1978 and had widely application in analyzing the relative effectiveness of the same department. But the weakness of the DEA-CCR model is that it assumes the constant returns to scale. Based on the DEA-CCR model, Banker et al. [31] proposed the DEA-BBC model, which broadens the assumption and can estimate the Decision-Making Units (DMUs) technology efficiency with variable returns to scale. Furthermore, the DEA-BBC model can be divided into input-oriented model and output-oriented model. Researcher can select the suitable model based on different research condition and purpose. By analyzing the input-output variables of construction industry, we find that the input variables are easier to control than the output variables. So, this article selects the input-oriented DEA-BBC method to analyze carbon dioxide emissions from construction industry.

If there are n Decision-Making Units (DMUs), for any decision-making unit (DMU), the input-oriented dual form of the DEA-BBC model can be expressed as follows:

$$\begin{aligned} \min \quad & \theta \\ \text{s.t.} \quad & \begin{cases} \sum_{j=1}^n X_j \lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^n Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, S^-, S^+ \geq 0 \end{cases} \end{aligned} \tag{1}$$

From the equation (1), $j = 1, 2, L \dots, n$ is the Decision-Making Units and X and Y are input vectors and output vectors, respectively. $\theta(0 \leq \theta \leq 1)$ represents the total efficiency of DMUs, λ is the coefficient of variable.

If $\theta = 1, S^+ = S^- = 0$, then the DMUs are effective

If $\theta = 1, S^+ \neq 0$ or $S^- \neq 0$, then the DMUs are weak effective

If $\theta < 1$, then the DMUs are ineffective

The performance of decision-making units (DMUs) is influenced by managerial inefficiencies, external environmental effects, and random errors. Here, the managerial inefficiencies is the inefficiencies which is caused by unsuitable management behavior; the external environmental effects is the influence of different luck on production efficiency, and random errors is the errors in the statistical model. When evaluating the performance of DMU, it is necessary to eliminate the influence of external environmental and random error and obtain the influence on production efficiency, which is caused only by management behavior.

3.2. The Second Stage: SFA Regression Analysis to Eliminate External Environmental Effects and Random Errors. The slack variables of input or output derived from the traditional DEA model are composed of environmental factors, managerial inefficiencies, and random errors. But traditional DEA model does not distinguish the three influences factors. By building SFA model, we can recognize the above three influence factors separately and remove the environmental factors and random factors, then get the slack value induced by managerial inefficiencies only [36]. The SFA model is established as follows:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni}; \quad i = 1, 2, \dots, I; n = 1, 2, \dots, N. \tag{2}$$

In equation (2), S_{ni} is the n^{th} input slack variable of DMU i^{th} ; $Z_{1i} = (z_{1i}, z_{2i}, \dots, z_{ki})$ is k environment variables; β_n refer to the coefficient of environment variables; $v_{ni} + \mu_{ni}$ is the mixed error; v_{ni} is random error and $v_{ni} \sim (0, \sigma_{vn}^2)$ obeys a truncated normal distribution; μ_{ni} is management inefficiency and obeys a truncated normal distribution, i.e. $\mu_{ni} \sim (\mu, \sigma_{vn}^2)$, and v_{ni} is independent from and uncorrelated to μ_{ni} . Suppose $\gamma = \sigma_{vn}^2 / (\sigma_{vn}^2 + \sigma_{\mu}^2)$, the influence of management factor predominates when γ closes to 1; the influence of random error predominates when γ closes to 0.

Influences of environmental factor and random error will be eliminated by adjusting the input of each DMU with the result of SFA regression. For example, adding the DMUs inputs, which are in better environment or with a good fortune. Then, the final efficiency value purely reflecting the DMUs' management level is calculated. Based on the best efficient DMU, the adjustments of other DMUs' inputs are as follows:

$$X_{ni}^A = X_{ni} + \left[\max \left(f \left(Z_i; \hat{\beta}_n \right) \right) - f \left(Z_i; \hat{\beta}_n \right) \right] + [\max(\nu_{ni}) - \nu_{ni}] \quad i = 1, 2, \dots, I; n = 1, 2, \dots, N. \quad (3)$$

In equation (3), X_{ni}^A represents adjusted input value, and X_{ni} represents original input value. $[\max(f(Z_i; \hat{\beta}_n)) - f(Z_i; \hat{\beta}_n)]$ is the adjustment to the external environment and $[\max(\nu_{ni}) - \nu_{ni}]$ is the adjustment to the random errors; thus, all DMUs have the same environmental factors and opportunity.

3.3. The Third Stage: Re-Estimating the Technology Efficiency by the Adjusted DEA Model. In the third stage, the adjusted input X_{ni}^A and original outputs are taken into the DEA-BCC model to estimate the technology efficiency value of each DMU. Therefore, it is the efficiency value eliminating the influence of environmental factors and random errors, which reflects truly the management efficiency and the technology efficiency of each DMU.

3.4. Variables Selection and Data Source

3.4.1. Selection of the Input Variables. Labor Force, Capital, and Technical Equipment are selected as input variables in this article.

- (1) *Labor Force.* As a labor-intensive sector, the quality and quantity of Labor Force heavily influence the efficiency of construction industry [37, 38]. So the Labor Force is selected as an input variable. Labor Force is represented by employees in the construction enterprises of each province over the years.
- (2) *Capital.* Capital is the critical strength to prompt the development of construction industry. Scholars [39, 40] select assets of construction enterprises as the Capital input variable to calculate the efficiency of construction industry. Following the scholars' researches above, the assets of construction enterprises in each province is selected as the Capital input variable. Considering the inflation, the assets of construction enterprises is adjusted to actual value according to the consumer price index using 2010 as the base period.
- (3) *Technical Equipment.* Manual and semimanual operations are one of the characters of construction industry. Capacity of construction machinery and equipment not only reflects the technological progress of the construction industry but also significantly influences the productivity and carbon dioxide emissions from the construction industry. Therefore, this article takes capacity of machinery and equipment owned by construction enterprises in China as the Technical Equipment input variable.

3.4.2. Selection of the Output Variables. The outputs of construction industry will be divided into desirable outputs

and undesirable outputs. Desirable outputs refer to the outputs that are beneficial to the goals and meets expectations, such as income, profits, gross production, and the like. Undesirable outputs, as the accompaniment of desirable output, are not beneficial to the goals and are not inconsistent with expectations, such as carbon dioxide emissions. The DEA-BCC model requires a positive correlation between output variable and input variable, but the carbon dioxide emissions are the negative correlation with input variables. Considering that the carbon dioxide emission is an accompanying desirable output, the article selects the Floor Space under Construction as the output variable from the physical perspective and the Production per Carbon Dioxide Emissions as output variable from an economic perspective.

Because the government does not issue the carbon dioxide emissions data from the construction industry, we should estimate the data. This study estimated the carbon dioxide emissions by energy consumption from construction industry in each region. The formula is as following:

$$CDE = \sum_{i=1}^n Q_i \times \delta_i. \quad (4)$$

In equation (4), CDE (carbon dioxide emissions) refers to the carbon dioxide emissions from the construction industry; Q_i (quantity) refers to the annual consumption of energy i of the construction industry; δ_i refers carbon dioxide emissions factor of energy i .

Energy consumptions are expressed in the standard coal of 10000 tons, which are converted by the energy consumptions from construction industry in each region (Table 1).

The factors of carbon dioxide emissions are determined with "the Intergovernmental Panel on Climate Change (IPCC) carbon dioxide emissions calculation guide (2006)," "Chinese Academy of engineering, the State Environmental Protection Administration of greenhouse gas control projects," and "the State Science and Technology Commission on climate change project of China" (Table 2).

3.4.3. Selection of Environmental Variable. Environmental variables refer to the uncontrollable factors that affect the efficiency of China's construction industry. Based on the existing relevant researches [41] and the features of construction industry, the authors select the following variables as environmental variables.

- (1) *Per Capita GDP.* The carbon dioxide emission efficiency from the construction industry is closely related to the per capita GDP of each region. If the GDP Per capita is higher, the construction industry may have higher carbon dioxide emission efficiency because of the good environment condition.
- (2) *Industrial Structure.* The industrial structure refers to the proportion of construction industry in the national economy. Generally, the higher Industrial

TABLE 1: Conversion coefficient from physical unit to coal equivalent.

Energy	Coal	Coke	Crude oil	Gasoline	Kerosene	Diesel	Fuel oil	Natural gas	Electricity
Conversion coefficient	0.686	0.971	1.429	1.471	1.471	1.457	1.429	13.3	1.229
Unit	tce/t	tce/t	tce/t	tce/t	tce/t	tce/t	tce/t	tce/10 ⁴ m ³	tce/10 ⁴ kWh

TABLE 2: The factor of carbon dioxide emissions of important building energy (tc/tce).

Energy	Coal	Coke	Crude oil	Gasoline	Kerosene	Diesel	Fuel oil	Natural gas	Electricity
The factor	0.725	0.855	0.540	0.554	0.571	0.592	0.619	0.427	0.275

Structure is, the greater output from construction industry is.

- (3) *Urbanization*. The rapid urbanization in China not only stimulates the demand for housing and infrastructure but also absorbs many labor forces into the construction industry.

All of the variables are shown in Table 3. The calculation and analysis of data are used by the software DEAP2.1 and Frontier4.1.

3.5. *Data Sources*. The study selected 30 provinces data of construction industry from 2010 to 2019 as sample. Due to the missing of data, the Tibet Autonomous Region are unselected. All data are grouped into three regions: Eastern region (Beijing, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Hainan, Heilongjiang, Jilin, and Liaoning), Middle region (Inner Mongolia, Shanxi, Henan, Hubei, Hunan, Jiangxi, and Anhui), and Western region (Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, Xinjiang, and Qinghai). These three regions represent the different economic development levels. Every region is considered as a DMU to estimate the carbon dioxide emission efficiency changing in China’s construction industry. All data in this article are from China statistical yearbook on construction (2011–2020), China statistical yearbook (2011–2020), and China statistical yearbook on energy (2011–2020). Variables measured in money in the article are adjusted by the Consumer Price Index (CPI) in 2011 to eliminate the influence of inflation.

4. Results and Discussion

4.1. *Empirical Analysis of the First-Stage DEA*. Taking input and output variables into the DEA-BCC model, this study analyzed the carbon dioxide emission efficiency from construction industry for three regions from 2010 to 2019 by DEAP2.1 software. It can be seen that the carbon dioxide emission efficiency of China’s regional construction industry has not reached the frontier either as whole or as region from 2010 to 2019 (Table 4). The technology efficiency (TE) value of China’s regional construction industry ranges from 0.75 in 2010 to 0.79 in 2014 and then to 0.74 in 2019. The average technology efficiency (TE) value is 0.70, which is a 30-percentage point from the technological frontier. Among the regions, the Eastern region has the highest technology efficiency value and the Western region has the lowest

technology efficiency value. Overall, the carbon dioxide emission efficiency of China’s regional construction industry is low and has a lot to improve. The mean of scale efficiency (SE) are more than 0.9 in most years except 2011, so the scale efficiency (SE) is close to the efficiency frontier. While the pure technical efficiency (PTE) ranges only from 0.72 to 0.81 in the years between 2010 and 2019, the lower technology efficiency (TE) and pure technology efficiency (PTE) restricts the carbon dioxide emission efficiency of all regions. However, this analysis includes the interference of environmental factors and random factors, which cannot reflect the real technical efficiency of carbon dioxide emission in various regions, so it needs to be further adjusted and recalculated.

4.2. *SFA Regression Analysis in the Second Stage*. Taken the slack variable of each input as dependent variables and the environment variables as independent variables, the Stochastic Frontier Analysis (SFA) model can be constructed to separate the influence of environmental factors, random errors, and management inefficiency. Then, based on equations (2) and (3), the slack variable of Labor Force, the slack variable of Capital, and the slack variable of Technical Equipment are taken as the dependent variables, and the three environment variables are taken as independent variables. The SFA regression results by FRONTIER 4.1 software are shown in Table 5.

According to Table 5, Per capita GDP to all of the three slack variables is significant at 5% and 1%. Industrial Structure to slack variable of Labor Force is significant at 5%, whereas the slack variable of Capital and the slack variable of Technical Equipment is significant at 1%. Urbanization to all of the three slack variables is significant at 1%. It indicates that the environmental factors significantly influence on the inputs slack variables; therefore, the data reported here is suitable for further regression analysis using SFA model. Furthermore, the influence of environmental variables on the carbon dioxide emission efficiency of the construction industry can be interpreted as follows:

- (1) The regression coefficients of Per capita GDP to the three slack variables are all positive, which indicates that the improvement in Per capita GDP will increase the slack of inputs and then decrease the carbon dioxide emission efficiency of construction industry.
- (2) The regression coefficient of Industrial Structure to the slack variable of Labor Force is positive, indicating that improvement in the proportion of the construction industry will increase the Labor

TABLE 3: Variables influencing the carbon dioxide emission efficiency of construction industry.

Type of variables	Variable	Explain
	Production per carbon dioxide emissions	GDP/carbon dioxide emissions of construction industry
Output	Floor space under construction	Housing construction area of construction projects under construction during the reporting period
Input	Labor force	Employees in the construction enterprises
	Capital	The assets of construction enterprises
	Technical equipment	Total capacity of machinery and equipment owned by construction enterprises
Environment	Per capita GDP	GDP/total population
	Industrial structure	GDP of construction industry/GDP
	Urbanization	Urban population/total population

Force slack and then decrease the carbon dioxide emission efficiency of construction industry. The regression coefficient of Industrial Structure to slack variable of Capital and the slack variable of Technical Equipment are negative, indicating that improvement in the proportion of the construction industry will increase the operating efficiency of funds and technology machinery, which are the important ways to improve the carbon dioxide emission efficiency of construction industry. (3) The regression coefficients of the Urbanization to the three dependent variables are negative. It shows that improvement in the Urbanization can reduce the inputs slack and then improve the carbon dioxide emission efficiency of construction industry. The reason is that China's urbanization is characterized by intelligence, low carbon, ecological livability, and government puts forward mandatory requirements for carbon emissions from the construction industry.

4.3. Analysis with Adjusted Inputs in the Third Stage. Taking the adjusted input values in the second stage and original output values into the DEA-BCC model again, we can get the more accurate carbon dioxide emission efficiency value of construction industry from 2010 to 2019 (Table 6).

From Tables 4 and 6, it can be seen that the values of carbon emission efficiency of regional construction industry in the third stage have changed significantly compared with the first stage. The mean values of TE are higher than the first stage in 2011 and 2012 and lower in other years than the values at the first stage. The mean values of PTE are higher than the first stage in the years. The mean values of SE are higher than the first stage in 2011 and 2012 and lower in other years than the first stage. It indicates that the carbon dioxide emission efficiency of regional construction industry is overestimated or underestimated in the first stage, and it is reasonable to adjust the original input values to eliminate the influence of environmental factors and random errors.

On the whole, the technology efficiency values of carbon dioxide emissions of construction industry in China are low and fluctuate in an upward firstly, then downward trend in third stage (the mean of TE increases from 0.67 in 2010 to 0.76 in 2014 then downward to 0.66 in 2019). The pure technical efficiency values have a fluctuating in an upward trend. In general, the scale

efficiency values have also increased firstly and then there was a downward trend (the mean of SE increased from 0.84 in 2010 to 0.93 in 2014, then decreased to 0.77 in 2019). China's regional construction industry has a low technology efficiency and pure technical efficiency and high scale efficiency in carbon emissions, which means the development of China's construction industry depends heavily on the scale expansion and lacks technological innovation.

From the perspective of efficiency category, the Eastern region has the highest technology efficiency values of carbon dioxide emissions among the three regions, followed by the Middle region and the West region. The gap of the technology efficiency is large in the three regions and is getting bigger year by year (Figure 1).

The Eastern region has the highest pure technology efficiency, followed by the West region and the Middle region before 2016, but the middle region has the higher technology efficiency than the West region (Figure 2).

The scale efficiency values in East region and Middle region are close to the efficiency frontier (the value ≥ 0.80). Western region has the lowest scale efficiency among the three regions and has a down growth in the scale efficiency (Figure 3).

From the regional perspective, the Eastern region has the highest technology efficiency and the highest pure technology efficiency among the three regions; the scale efficiency of Middle region is overtaken by Eastern region after 2017. It indicates that the East region, supported by developed economy, abundant capital, and high-quality labor force, does better in increasing the carbon emission efficiency of construction industry than the other regions. Meanwhile, the technology efficiency, the pure technology efficiency, and the scale efficiency of Eastern region have no significant change from 2010 to 2019, indicating that the carbon dioxide emission efficiency of the Eastern region has little improvement. The reason may be that the construction enterprises in the eastern region indulge in the current situation and have no motivation to take further measures to improve green construction technology. Therefore, the low-carbon technologies should be developed and the clean technology equipment should be invested for the Eastern region to keep ahead in carbon dioxide emission efficiency. On the whole, the carbon dioxide emission efficiency of the Eastern region is the highest in the three regions.

TABLE 4: The carbon dioxide emission efficiency of regional construction industry in the first stage DEA.

	2010		2011		2012		2013		2014		2015		2016		2017		2018		2019											
	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE	TE	PTE	SE									
Eastern region	0.81	0.82	0.98	0.70	0.82	0.83	0.77	0.84	0.91	0.80	0.84	0.96	0.84	0.86	0.98	0.83	1.00	0.82	0.83	1.00	0.80	0.81	0.99	0.84	0.85	1.00	0.87	0.87	1.00	
Middle region	0.71	0.72	0.98	0.58	0.71	0.81	0.70	0.75	0.92	0.72	0.74	0.97	0.78	0.79	0.99	0.74	1.00	0.74	0.74	0.99	0.71	0.72	0.99	0.69	0.69	0.99	0.72	0.73	0.99	
Western region	0.71	0.77	0.94	0.54	0.67	0.79	0.65	0.73	0.89	0.69	0.74	0.93	0.75	0.79	0.96	0.73	0.74	0.98	0.68	0.71	0.96	0.60	0.64	0.95	0.58	0.63	0.94	0.62	0.66	0.95
Mean	0.75	0.78	0.97	0.61	0.74	0.81	0.70	0.77	0.90	0.74	0.78	0.95	0.79	0.81	0.98	0.77	0.78	0.99	0.75	0.76	0.98	0.71	0.72	0.98	0.71	0.73	0.97	0.74	0.76	0.98

Note. TE refers technical efficiency, PTE refers pure technical efficiency, SE refers scale efficiency, TE = PTE* SE.

TABLE 5: SFA regression results.

	Slack variable of labor force			Slack variable of capital			Slack variable of technical equipment		
	Coefficient	Standard-error	T-ratio	Coefficient	Standard-error	T-ratio	Coefficient	Standard-error	T-ratio
Constant value	1.53E+01	1.62E+00	9.42E+00***	3.98E+01	3.37E-01	1.18E+02***	2.11E+01	5.03E-01	4.21E+01***
Per capita GDP	5.85E+00	2.57E+00	2.28E+00**	2.97E+01	7.29E-01	4.07E+01***	1.37E+01	2.76E-01	4.95E+01***
Industrial structure	2.14E+01	1.03E+00	2.09E+01**	-5.20E+01	9.92E-01	-5.24E+01***	-1.96E+02	9.95E-01	-1.97E+02***
Urbanization	-7.71E+01	1.24E+00	-6.20E+01***	-2.09E+02	9.47E-01	-2.21E+02***	-5.50E+01	9.55E-01	-5.76E+01***
Sigma squared	1.50E+03	1.00E+00	1.50E+03***	1.58E+05	1.00E+00	1.58E+05***	8.40E+04	1.00E+00	8.40E+04***
Gamma	1.00E+00	8.69E-06	1.15E+05***	1.00E+00	2.68E-07	3.74E+06***	1.00E+00	3.65E-07	2.74E+06***
Log likelihood function		-0.13014126E+03			-0.19777372E+03			-0.18850616E+03	
LR test of the one-sided error		0.16321106E+02			0.20882593E+02			0.20445934E+02	

Notes: *** significant at 1%, ** significant at 5%, * significant at 10%.

TABLE 6: The Comparison of the carbon dioxide emission efficiency adjusted inputs in the third stage.

	2010		2011		2012		2013		2014		2015		2016		2017		2018		2019											
	TE	SE	TE	SE	TE	SE	TE	SE	TE	SE	TE	SE	TE	SE	TE	SE	TE	SE	TE	SE										
Eastern region	0.74	0.82	0.91	0.79	0.83	0.96	0.79	0.82	0.97	0.78	0.83	0.94	0.80	0.86	0.94	0.78	0.84	0.93	0.75	0.84	0.89	0.77	0.81	0.96	0.75	0.86	0.88	0.78	0.89	0.86
Middle region	0.67	0.74	0.91	0.72	0.74	0.97	0.70	0.71	0.98	0.74	0.76	0.97	0.78	0.80	0.97	0.72	0.77	0.93	0.72	0.80	0.89	0.71	0.74	0.95	0.65	0.79	0.80	0.68	0.83	0.81
Western region	0.61	0.86	0.73	0.68	0.83	0.83	0.72	0.76	0.94	0.70	0.78	0.91	0.71	0.81	0.88	0.65	0.82	0.82	0.58	0.79	0.75	0.58	0.68	0.87	0.50	0.79	0.65	0.53	0.82	0.66
Mean	0.67	0.81	0.84	0.73	0.80	0.92	0.74	0.77	0.96	0.74	0.80	0.94	0.76	0.83	0.93	0.72	0.81	0.89	0.68	0.81	0.84	0.69	0.74	0.93	0.63	0.82	0.77	0.66	0.85	0.77

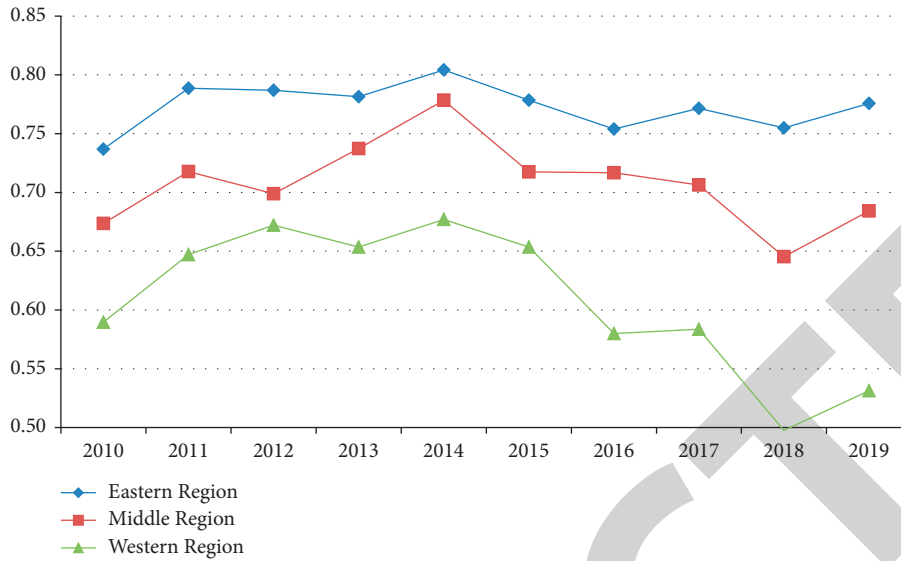


FIGURE 1: Comparison of technology efficiency (TE) of carbon emission in regions in the third stage from 2010 to 2019.

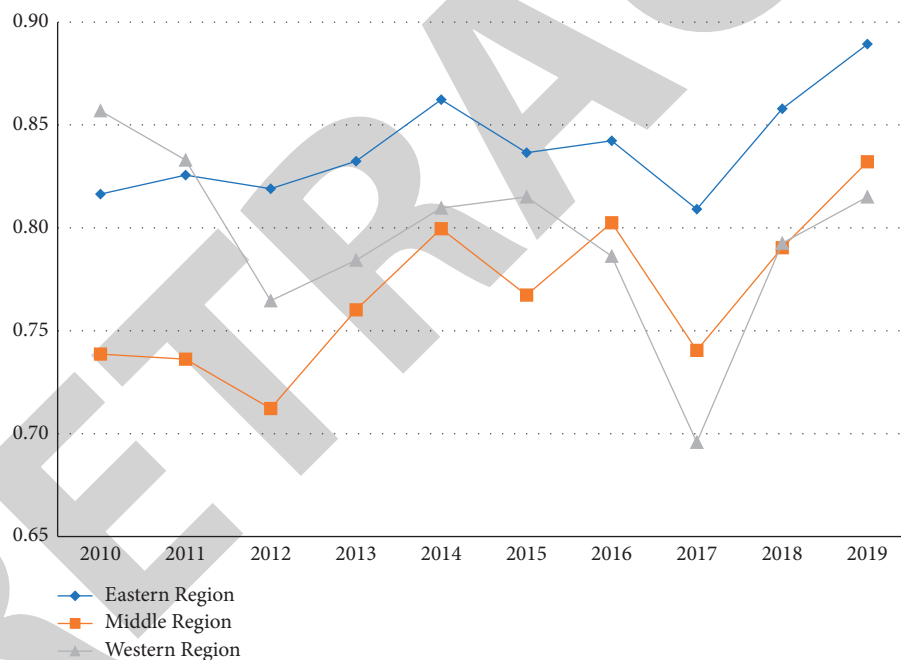


FIGURE 2: Comparison of the pure technology efficiency (PTE) of carbon emission in regions in the third stage from 2010 to 2019.

The technology efficiency in the Middle region has an uptrend in fluctuation, the pure technical efficiency is the lowest before 2016 in the three regions, and the scale efficiency is the highest before 2017. The Middle region should learn advanced management from the East region, enhance innovation ability, and adopt the high-tech equipment to improve the pure technical efficiency.

The technology efficiency and the pure technical efficiency in the Western region show a downward tendency;

the scale efficiency is the lowest but is rising rapidly, indicating that the inefficiency of carbon dioxide emissions of the Western region is mainly due to lower scale efficiency. Comparing with other regions, it is obvious that the Western region is fairly undeveloped, with much land and few people. Therefore, the Western region should also learn the advanced management method from the Eastern region, improve the ability of labor force, and adopt the high-tech equipment to increase its carbon emission efficiency.

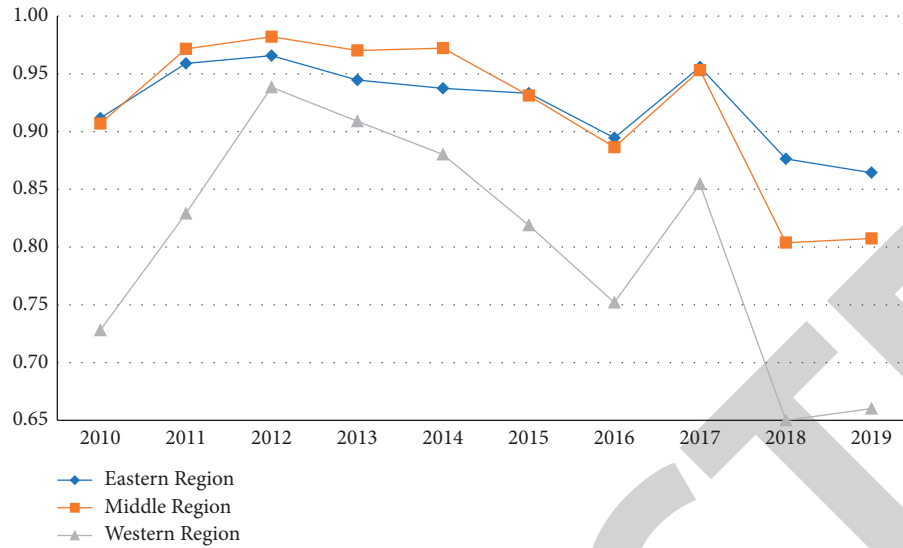


FIGURE 3: Comparison of scale efficiency (SE) of carbon emission in regions in the third stage from 2010 to 2019.

5. Conclusion

This study researches the carbon emission efficiency in China's construction industry and its regional difference by the third stage DEA model from 2010 to 2019. The conclusions can be drawn as follows:

- (1) Eliminating the impact of environmental factors and random errors, the technology efficiency values, the pure technical efficiency values, and the scale efficiency values of carbon dioxide emissions of regional construction industry in China have large changes compared with the values in the first stage. It means that the efficiency of carbon dioxide emissions in regional construction industry is overestimated or underestimated in the first stage. Thus, it is reasonable to adjust the original inputs value by environmental variables.
- (2) The environmental variables have an influence on the carbon emission efficiency of construction industry in China. The improving of Per capita GDP will increase heavily inputs slack and environmental pollution. The improvement in Industry Structure will significantly increase the slack variable of Labor Force and decrease the slack variable of Capital and Technical Equipment. The improvement in Urbanization can decrease the inputs slack and then increase the carbon emission efficiency.
- (3) After adjusted, the technology efficiency values of carbon dioxide emissions are low in whole and different among the three regions, indicating that there is the big room for China's construction industry to improve the efficiency of carbon dioxide emissions. The government and enterprises should work hard to achieve the goal of green development in China's construction industry. Besides, the scale efficiency of the three regions is all close to the efficiency frontier. So, the pure technology

efficiency is the bottleneck restricting the carbon dioxide emission efficiency.

- (4) It is necessary to narrow the gap of carbon dioxide emission efficiency among the regions. The Eastern region with developed economic and high-tech should take more responsibility in reducing carbon dioxide emissions and play a leading role in the spreading the low-carbon technologies to other regions. The Middle region and the Western region should learn the advanced management methods from Eastern region and adopt the high-tech equipment to improve the carbon dioxide emission efficiency. The key method to improve carbon dioxide emission efficiency is to improve management level and apply high technology to change the growth mode of the construction industry. So, the construction enterprises should actively develop new low-carbon technology and participate in international technical cooperation to improve the level of technology and management. The government should provide financial support or tax incentives for the construction enterprises, which have the higher carbon emission efficiency or apply low-carbon technology.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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