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Environmental Regulation, Technological Progress and Carbon Emission Efficiency: An Empirical Analysis Based on Panel Data of Chinese Provinces

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Abstract: China faces the key issue of improving the efficiency of carbon emissions, in its endeavor of building a low-carbon economy and reducing carbon emissions. This paper adopts the super-slack-based measure (SBM) model with a bad output to measure the carbon emission efficiency of each Chinese province from 2000 to 2019, and further uses the Tobit model to analyze the impact of environmental regulation, technological progress, and the interaction between the two on carbon emission efficiency. The results show that: China's carbon emission efficiency presents a large inter-provincial difference. Only a few provinces like Shanghai and Beijing reached the efficient frontier, while all the other provinces failed to do so. Overall, most Chinese provinces have a huge potential for improving carbon emission efficiency. By dividing China into three regions, it could be seen that the eastern region had the highest carbon emission efficiency, followed in turn by the central region and the western region. According to the spatiotemporal variation of carbon emission efficiency, most provinces with a high carbon emission efficiency belong to the economically developed eastern region, while most central and western provinces did not realize satisfactory carbon emission efficiency. With the elapse of time, the carbon emission efficiency in most provinces declined to varied degrees, while that of a few provinces was on the rise. The results of the Tobit model show that both environmental regulation and technological progress both significantly promoted carbon emission efficiency, but their cross term clearly suppressed carbon emission efficiency. When it comes to the control variables, carbon emission efficiency has a significantly positive relationship with opening-up, and a significantly negative relationship with industrial structure, financial development, energy structure, and urbanization level.

Keywords: Environmental regulation; Technological progress; Carbon emission efficiency; Super-SBM model; Tobit model

1. Introduction

As the greenhouse effect intensifies across the globe, countries around the world are paying more attention to the reduction of carbon emissions. Since the adoption of the reform and opening-up policy over four decades ago, China has witnessed rapid economic growth, and developed into the second largest economy in the world. Nevertheless, carbon dioxide emissions become a severe problem, owing to the long-term extensive model of economic development, which features high energy consumption, high investment, and high emissions. The Energy Agency announced that China overtook the United States as the world's largest carbon emitter in 2009 (Wang & Ma, 2018). Currently, China emitted 27.3% of all carbon dioxide globally, greater than the emissions of the second and third largest emitters combined, namely, the United States (16%) and India (6.8%) (Wang et al., 2019). To promote global decarbonization, China announced two goals at the 75th United Nations General Assembly: it will strive carbon emissions before 2030, and neutralize carbon emissions prior to 2060. The country needs to cope with a tremendous pressure to realize the two goals. However, the primary task of China, as the largest developing country, is to pursue economic development. It is a major issue for the Chinese government to achieve the goals of carbon reduction, while ensuring economic development. In the future, improving the carbon emission efficiency will be the main pathway to balance economic development and carbon emissions. Then, it is necessary to find answers to the following questions: How high is the carbon emission efficiency of each Chinese province? What are the factors affecting the carbon emission efficiency?

For a long time, how to promote carbon emission reduction has been the focus of academic circles. Many researchers probed deep into the relationship between environmental regulation and carbon dioxide emissions. For example, Pei et al. (2019), Wu et al. (2020a), Xu & Xu (2022) demonstrated that environmental regulation benefits carbon emission reduction. Zhang et al. (2021) and Wang & Zhang (2022) found the inverted U-shaped relationship between environmental regulation and carbon dioxide emissions in China. In addition, a few scholars concerned about the important impact of environmental regulation on carbon productivity. Du & Li (2020) analyzed the combined data of the Chinese Industrial Enterprise Database and the Chinese Enterprise Environmental Survey and Reporting Database, and discovered that environmental regulation policies promote the coordinated emission reduction of pollutants and greenhouse gases. There is also direct evidence that environmental regulation boosts carbon productivity. Zhou & Tang (2021) investigated environmental regulation and carbon productivity in China, and learned that environmental regulation bears on the growth of total factor carbon productivity in air pollution-intensive industries. Song & Han (2022) explored the bilateral effects of command-and-control-based and market-based environmental regulations on carbon productivity, and made the following discoveries: the net effect of command-and-control-based environmental regulation on carbon productivity was−0.0541, and that of market-based environmental regulation on carbon productivity was 0.0653. The above studies show that most scholars concluded that environmental regulation has a positive impact on carbon dioxide emissions and carbon productivity. This provides indirect evidence that environmental regulation is beneficial to improving carbon emission efficiency.

Some scholars noticed the relationship between technological progress and carbon emission efficiency. For example, Wang et al. (2019) confirmed that continuous technological progress is the main reason for the different degrees of improvement in carbon dioxide emission efficiency. Du & Li (2019) found that green technology innovation significantly improves the total factor carbon productivity of economies with income levels above the threshold, but has little effect on economies with a low income. Li & Cheng (2020) pointed out that the clearly heterogenous impacts of technological progress on carbon emission efficiency between industrial sectors. Using the super-slack-based measure (SBM) model, Xie et al. (2021) evaluated the carbon emission efficiency of 59 countries from 1998 to 2016, with the aim to disclose the multiple impacts of technological progress on the carbon emission efficiency of countries with different efficiency levels. The results show that technological progress drives carbon emissions efficiency significantly, but this driving effect varies across countries with different levels of efficiency. You & Zhang (2022) used a panel data model to study the impact of heterogeneous technological progress levels on the industrial carbon efficiency of 30 Chinese provinces, and observed that: the carbon efficiency can be better improved by the technological advances in energy than those in carbon emissions; the carbon efficiency can be better improved by neutral technological advances than capital embodied technological advances. Based on the panel data of 285 Chinese cities of 2011-2017, Zhang & Liu (2022) applied a spatial econometric model to analyze the impact of digital finance and green technology innovation on carbon emission efficiency, and discovered the important role of the synergy between the two factors on promoting local carbon emission efficiency. Through data envelopment analysis (DEA), Zhao et al. (2022) estimated the transport sector carbon dioxide emission efficiency (TSCDEE) of 30 Chinese provinces in 2010-2016, and analyzed the factors affecting TSCDEE with the spatial Durbin model. The results show that factors like technological progress significantly promotes TSCDEE. In summary, different scholars resorted to different metrics of technological progress, and differed slightly in conclusions. Overall, most studies agree that technological progress significantly promotes carbon emission efficiency.

This study makes breakthroughs in two aspects: Firstly, the existing studies focus on the impact of environmental regulation on carbon emissions or carbon productivity, paying limited attention to the effect of environmental regulation on carbon emission efficiency. This gap is filled by this research. Secondly, the previous literature emphasizes on the relationship between technological progress and carbon emission efficiency. However, there is virtually no report on how environmental regulation, technological progress, and their interplay affect carbon emission efficiency. To solve the problems, this paper adopts the Super-SBM model to measure the carbon emission efficiency of each Chinese province, and further utilizes the Tobit model to examine the relationship between environmental regulation, technological progress, and carbon emission efficiency, thereby filling the gaps in the previous works.

2. Materials and Methods

2.1 Methodology

2.1.1 Super-SBM model

Currently, efficiency evaluation is mainly carried out using two types of models: DEA and stochastic frontier analysis (SFA). As a typical parametric method, SFA needs a production function, and only evaluates efficiency problems with multiple outputs and a single output. As a result, SFA is not as flexible and adaptive as DEA. Hence, this paper chooses DEA to measure the carbon emission efficiency of Chinese provinces. As a representative nonparametric method, DEA constructs the optimal production frontier through linear programming, and projects each production unit onto that frontier, thereby evaluating the efficiency of the decision-maker. It is a typical systematic analysis approach for relative efficiency involving multiple inputs and multiple outputs. Since its nascence, DEA has been constantly evolving. The earliest versions of DEA are CCR with constant returns and BCC with variable returns (Banker et al., 1984; Charnes et al., 1978). Both models are radial models, requiring the inputs and outputs to change in the same direction by the same proportion, during the efficiency improvement. Adhering the principle of maximizing the outputs, these models face a common problem: the efficiency cannot be improved unless good and bad outputs increase at the same time. This clearly goes against the reality. It can be said that the radial models cannot effectively solve the problem of bad outputs. When carbon dioxide is taken as the bad output, it is impossible to evaluate carbon emission efficiency correctly, using the traditional CCR and BCC models. To address the problem of bad outputs, Morita et al. (2005) proposed the non-radial, non-angular SBM model, which solves the problem of the traditional radial models (i.e., requiring the inputs and outputs to change in the same direction by the same proportion). The SBM model is more accurate in measuring the efficiency involving bad outputs than the traditional models.

Although capable of solving the bad output problem, the SBM model may have some defects. Specifically, the efficiency of each decision-maker measured by the SBM model cannot surpass one. Thus, it is possible that multiple decision-makers may end up with the efficiency of one. Then, there is no meaning to compare these decision-makers. To breakthrough this limitation, Andersen & Petersen (1993) presented the idea of super efficiency programming. The most prominent advantage of their idea is allowing the efficiency of decision-makers to surpass one, making the comparison between decision-makers more reliable and accurate. The super efficiency idea is later combined with the SBM to yield the Super-SBM model.

The Super-SBM model is constructed by the following principle: Suppose a production system is composed of n decision-makers. During the operation, the system needs to receive *i* production factors, and produce s1 good outputs and s2 bad outputs. To simplify the description, the input factor matrix *X*, good output matrix *Y*, and bad output matrix B of the system can be respectively defined as:

$$X=(x_1,x_2,...,x_n)\in R_+^{i\times n} \tag{1}$$

$$Y=(y_1,y_2,...,y_n)\in R_+^{s_1\times n} \tag{2}$$

$$B=(b_1,b_2,...,b_n)\in R_+^{s_2\times n} \tag{3}$$

The three matrices *X*, *Y* and *B* must all be greater than zero. If the returns to scale is constant, the possible set of production scenarios *T* can be defined as:

$$T=\left\{(x,y,b)\middle|x\geq X\lambda,\ y\leq Y\lambda,\ b\geq B\lambda,\sum\lambda=1\right\} \tag{4}$$

Based on the above conditions, DUM_k is the *k*-th decision-maker to be estimated. Then, the Super-SBM model containing bad outputs can be expressed as:

$$\begin{aligned}
&\kappa^*=\min\frac{1-\frac{1}{i}\sum_{h=1}^{i}\frac{s_h^-}{x_{hk}}}{1+\frac{1}{s_1+s_2}\left(\sum_{e=1}^{s_1}\frac{s_e^+}{y_{ek}}+\sum_{f=1}^{s_2}\frac{s_k^{b-}}{b_{fk}}\right)}\\
&s.t.\ x_{hk}\geq\sum_{\substack{j=1\\j\neq k}}^{n}x_{hj}\lambda_j-s_h^-,h=1,...,i\\
&\quad y_{ek}\leq\sum_{\substack{j=1\\j\neq m}}^{n}y_{ej}\lambda_j+s_e^+,e=1,...,s_1\\
&\quad b_{fk}\geq\sum_{\substack{j=1\\j\neq k}}^{n}b_{fj}\lambda_j-s_f^{b-},f=1,...,s_2\\
&\quad \lambda\geq 0,s_h^-,s_e^+,s_f^{b-}\geq 0
\end{aligned} \tag{5}$$

where, κ^* is the carbon emission efficiency to be measured; x_{hk}, y_{ek} and b_{fk} are the h-th input, e-th good output, and f-th bad output of DUM_k, respectively; s_h^-, s_e^+ and s_f^{b-} are the redundancy of inputs, insufficiency of good outputs, and redundancy of bad outputs, respectively; j is the j-th decision-maker; λ_j is the weight of the j-th decision-maker; objective function κ^* is a monotonically decreasing function about s_h^-, s_e^+, and s_f^{b-}. If $\kappa^* \geq 1$, the decision-maker has reached the optimal frontier, the state is optimal, and no improvement is needed; if $\kappa^* < 1$, the decision-maker faces an efficiency loss, and the slack term of the inputs must be adjusted, in order to improve the efficiency.

2.1.2 Tobit model

This study attempts to realize an important goal: how environmental regulation and technological progress affect carbon emission efficiency. Therefore, carbon emission efficiency was treated as the dependent variable in our measurement model. The efficiency was evaluated by the Super-SBM model. The results must be greater than zero, i.e., censored. Before variable regression, the traditional methods like the ordinary least squares (OLS) needs to meet an important premise: The dependent variable has no size limit. Otherwise, the traditional regression may cause the estimation result of the model to be biased towards zero, which will lead to a large deviation. To solve the problem of censored dependent variable, Tobin (1958) proposed the Tobit modulus:

$$y = \begin{cases} y_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon, & y_i > 0 \\ 0, & y_i \leq 0 \end{cases} \tag{6}$$

where, y_i is the carbon emission efficient of the decision-maker i, i.e., the dependent variable of the model; x_i is the independent variable (in total, there are n independent variables); β_0 is the intercept; β_i is the coefficient of each influencing factor; ε is the random error vector, which satisfies the normal distribution.

2.2 Variable Selection

2.2.1 Inputs and outputs

The carbon emission efficiency examined in this paper is a total factor efficiency, not a single factor efficiency. Drawing on Zaim & Taskin (2000), and Zhou et al. (2010), this paper defines carbon emission efficiency as follows: the efficiency of carbon emissions corresponding to the maximum economic output and the minimum carbon emissions, when the inputs (capital, labor, and energy) do not increase or change. On this basis, this paper establishes an evaluation index system for carbon emission efficiency, which is composed of inputs and outputs. Combined with the results of Zhang et al. (2022), there are three inputs: labor input, capital input, and energy input, and two outputs: good output and bad output. The good output refers to the GDP of each province, while the bad output is the carbon dioxide emissions of each province. Table 1 explains the inputs and outputs in the proposed system.

(1) Labor input

Labor is a key element of regional economic growth. Drawing on Zhang et al. (2022), this paper uses the year-end number of employees in each province to represent labor input.

(2) Capital input

The data of capital input cannot be obtained directly, for the relevant government departments have not given this data, and the variable is unlikely to be represented directly by any suitable index (Du et al., 2022). The common practice is to estimate the capital stock of each province. Drawing Zhang et al. (2017), this paper uses the Perpetual Inventory Method (PIM) to estimate the capital stock of each province:

$$K_{i,t} = I_{i,t} + (1-\delta)K_{i,t-1}$$

where, $K_{i,t}$ is the capital stock of region i in year t; $K_{i,t-1}$ is the capital stock of region i in year t-1; $I_{i,t}$ is the fixed capital formation of region i in year t; δ is the depreciation rate of the capital of region i in year t (here, this index equals 9.6%) (Yan et al., 2020). In addition, the nominal capital stock may be too high, due to the price factor. To solve the problem, this paper uses the fixed asset price index to deflate the nominal capital stock to the real capital stock with 2000 as the base period.

(3) Energy input

Drawing on the results of Cai & Fan (2019), this paper uses the total regional energy consumption to represent energy input.

(4) Good output

Drawing on the results of Wu et al. (2020b), this paper selects GDP as the good output. The data of nominal GDP in the relevant statistical yearbooks contain price factors. If they are used directly, inflation will ensue. To prevent inflation, this paper uses the GDP index to deflate nominal GDP to real GDP at comparable prices in 2000.

(5) Bad output

The bad output here is carbon dioxide. The relevant statistical yearbooks have not yet published the data. Drawing on Liang et al. (2021), this paper uses the calculation method of carbon dioxide published by IPCC (2006) to estimate the carbon dioxide emissions of various regions:

$$CO_2 = \sum_{i=1}^{n} \times NCV_i \times CEF_i \tag{7}$$

where, CO_2 is the carbon dioxide emissions to be estimated; i is each type of energy; n is the total number of energies. Considering the data availability, n was set to 11 for 2000-2009 to avoid repetitive calculations. The 11 energies refer to coal, coke, coke oven gas, other gases, crude oil, gasoline, kerosene, diesel, fuel oil, LPG and natural gas. For 2010-2019, three more energies were added, including blast furnace gas, converter gas and liquefied natural gas. E_i is the combustion consumption of the i-th energy; NCV_i is the average low-level calorific value of the i-th energy, which is used to convert various energy consumption into energy units (TJ); CEF_i is the carbon dioxide emission factor of the i-th energy.

Table 1. Input and output indices of carbon emission efficiency

	Variable	Description (unit)	Unit
Inputs	Labor input	Year-end number of employees of each province in the sample period	10,000 people
	Capital input	Actual capital stock of each province in the sample period with 2000 as the base period	100 million yuan
	Energy input	Total energy consumption of each province in the sample period	10,000 tons of standard coal
Outputs	Good output	Real GDP of each province in the sample period with 2000 as the base period	100 million yuan
	Bad output	Total carbon oxide emissions estimated for each province in the sample period	10,000 tons

2.2.2 Influencing factors

This paper focuses on the relationship between environmental regulation, technological progress and carbon emission efficiency. An important premise is to sort out the impact mechanism of environmental regulation and technological progress on carbon emission efficiency. In addition to the two important independent variables, i.e., environmental regulation and technological progress, a series of control variables must also be taken into consideration.

(1) Environmental regulation (ER).

Considering data availability, this paper uses the proportion of industrial pollution control investment to the industrial added value per 10,000 yuan to measure environmental regulation. Existing studies have shown that environmental regulation has two main effects on carbon emission efficiency: green paradox or forced emission reduction.

The green paradox means increasing the intensity of environmental regulation will intensify carbon emissions, which in turn suppresses the efficiency of carbon emissions. The main reason for the green paradox is that stricter environmental regulation will make energy miners expect stricter environmental policies in the future. Then, the miners will exploit fossil energy more quickly, and thus emit more carbon dioxide (Sinn, 2008; van der Ploeg & Withagen, 2013). Not only that, the government blindly sets up carbon tax policies, and implements policies to curb the demand for fossil energy. In reality, there will be a time lag between policy promulgation and implementation, which will also cause the green paradox. Grafton et al. (2012) also proved the existence of the green paradox. He found that the biofuel subsidy policy may lead to the decline of fossil fuel prices and increase the demand for fossil energy.

The forced emission reduction means the government uses environmental regulation tools to restrain and intervene in the pollutant discharge by enterprises, so as to promote enterprises to achieve energy conservation and emission reduction. By levying environmental taxes or pollution discharge fees, the government increases the pollution discharge cost of enterprises utilizing fossil energy, and reduces the income of enterprises using fossil energy. To improve economic benefits, enterprises have to reduce the amount of fossil energy used, and are forced to reduce emissions. Besides, the government implements clean energy or renewable energy subsidy policies, which motivate polluting enterprises to use clean energy instead of fossil energy. In addition, the government could enforce control over the number of pollutants discharged by enterprises by implementing mandatory orders. This measure will also promote enterprises to reduce carbon emissions. Lanoie et al. (2008), and Pan et al. (2018) found that high-intensity environmental regulation can improve production efficiency and reduce carbon dioxide emissions.

In short, the impact of environmental regulation on carbon emission efficiency remains uncertain. The uncertainty has much to do with the intensity of environmental regulation in specific regions.

(2) Technological progress (TP)

Considering the availability of data, this paper uses the ratio of internal expenditure of research and development (R&D) fund to GDP to represent technological progress. Technological progress has two important effects on carbon emission efficiency.

Firstly, technological progress positively affects carbon emission reduction. Lee & Min (2015), and Mensah et al. (2018) both highlighted the importance of R&D investment for carbon dioxide reduction. By increasing R&D investment to achieve technological progress, enterprises can improve their production processes and equipment, and gradually reduce the use of high-carbon energy. This reduction is conducive to reducing carbon dioxide emissions. Apart from that, technological progress produces the substitution effect of energy factors. In particular, the progress of low-carbon technology will prompt enterprises to gradually increase the use of clean energy, thereby increasing their energy conservation and emission reduction capabilities (Elliott & Shanshan, 2008).

Secondly, technological progress improves the human factors of the enterprise. With the growing technical level, the enterprises in a region needs to meet higher requirements for the quality of labor. On the one hand, workers can use more advanced low-carbon equipment; on the other hand, the workers become more aware of the importance of environmental protection, and can more actively fulfill their obligations to protect the environment (Hübler et al., 2012). In conclusion, technological progress has a positive impact on carbon emission efficiency.

(3) Cross term between environmental regulation and technological progress (*ER**TP*)

There is a close connection between environmental regulation and technological progress. Further interaction between environmental regulation and technological progress will have an important impact on carbon emission efficiency. However, studies have found that environmental regulation and technological progress interact in three distinctive ways:

Firstly, environmental regulation inhibits technological progress. The traditional view holds that, when technology, resource allocation and consumer demand are constant, environmental regulation increases the cost of pollution control of enterprises, which squeezes the R&D investment of enterprises and increases their operating costs. Hence, environmental regulation is not conducive to technological innovation (Chintrakarn, 2008; Gray, 1987).

Secondly, environmental regulation promotes technological progress. This view is mainly derived from Porter's hypothesis (Porter & Van der Linde, 1995). Environmental regulation increases the environmental cost of business operations through market incentives or administrative penalties. To meet the requirements of environmental protection, enterprises must carry out technological innovation activities. The improvement of technology will compensate for the operating cost of enterprises, thereby offsetting the price paid by enterprises to cover the cost of pollution control (Arimura & Sugino, 2007; Brunnermeier & Cohen, 2003; Greaker, 2003).

Thirdly, the relationship between environmental regulation and technological progress is uncertain. The relationship is determined by the comprehensive effect of multiple factors (Becker, 2011; Yuan & Xiang, 2018).

The above three different interactions between environmental regulation and technological progress determines that the cross term between the two factors has an uncertain effect on carbon emission efficiency.

(4) Other control variables

In addition to environmental regulation, technological progress, and their cross term, many other factors have an impact on carbon emission efficiency. Existing studies have shown that, industrial structure (IS) (Wang et al., 2019), financial development (FD) (Dong et al., 2022), opening-up (OU) (Liu et al., 2018a), energy structure (ES) (Sun & Huang, 2022), and urbanization level (UL) (Liu et al., 2018b) are major influencers of green total factor productivity. These control variables were measured as follows:

The IS was represented by the proportion of the output value of the secondary industry in the GDP of each province in China over the years; the FD was represented by ratio of the deposit balance to the loan balance of each province over the years; the OU was represented by the ratio of actual foreign direct investment to GDP, after converting the USD into RMB according to the average exchange rate; the ES was represented by the proportion of coal consumption to total energy consumption in each province over the years; the UL was represented by the proportion of the urban population to the total population of each province at the year end.

2.3 Data Sources

To ensure the data comprehensiveness and accuracy of each variable, this paper selects the panel data of 30 Chinese provinces from 2000 to 2019 as the research object. Note that Tibet, Hong Kong, Macau and Taiwan were not included, due to missing variable data for multiple years. The original data of all the above indices come from China Statistical Yearbooks (2001-2020), China Energy Statistical Yearbooks (2001-2020), China Population and Employment Statistical Yearbooks (2001-2020), China Environment Yearbooks (2001-2020), as well as the statistical yearbooks of each province. In addition, the few missing values in the panel data were completed through interpolation.

3. Results and Discussion

3.1 Measured Carbon Emission Efficiency

3.1.1 Static time series variation of carbon emission efficiency

According to the proposed input-output index system of carbon emission efficiency, this paper imports the data of variables like labor, capital, energy, GDP, and carbon dioxide into MaxDEA, and uses the Super-SBM model to measure the carbon emission efficiency of each province in China from 2000 to 2019.

For comparison, Figure 1 presents the carbon emission efficiency of each province in China from 2020 to 2019. It can be seen that China's carbon emission efficiency features large provincial differences.

During the sample period, the carbon emission efficiency of Beijing and Shanghai exceeded 1 in most years.

Guangdong, Fujian, Hainan, Zhejiang, and Hubei also performed relatively well in carbon emission efficiency: The mean carbon emission efficiency in the sample period was between 0.8 and 1. Geographically, all these provinces except Hubei are located in the eastern coastal areas of China.

Meanwhile, the mean carbon emission efficiency of other provinces was between 0.6 and 0.8, which is not satisfactory. The carbon emission efficiency of these provinces is far from the optimal frontier, and needs to be further improved in the future. In terms of location, these provinces are mainly distributed in the central and western regions. In particular, the mean carbon emission efficiency of Qinghai, Inner Mongolia, and Ningxia was lower than 0.5, a sign of relatively poor performance. These provinces should be the focus of carbon emission efficiency improvement in the future.

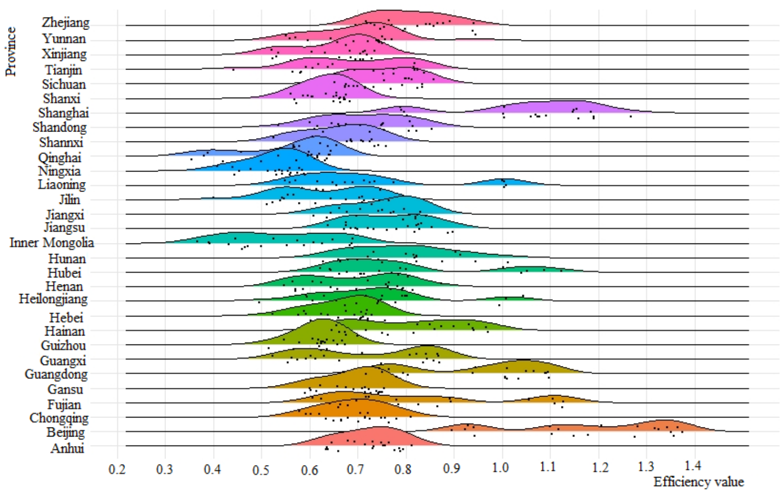


Figure 1. Provincial carbon emission efficiency in 2000-2019

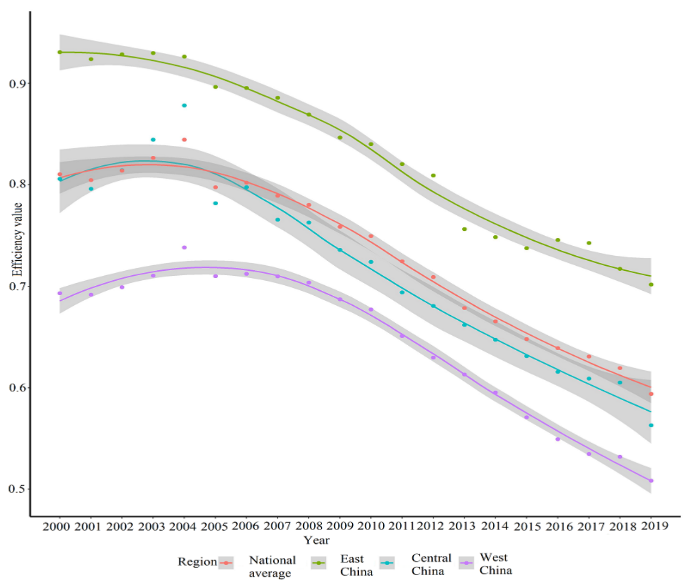


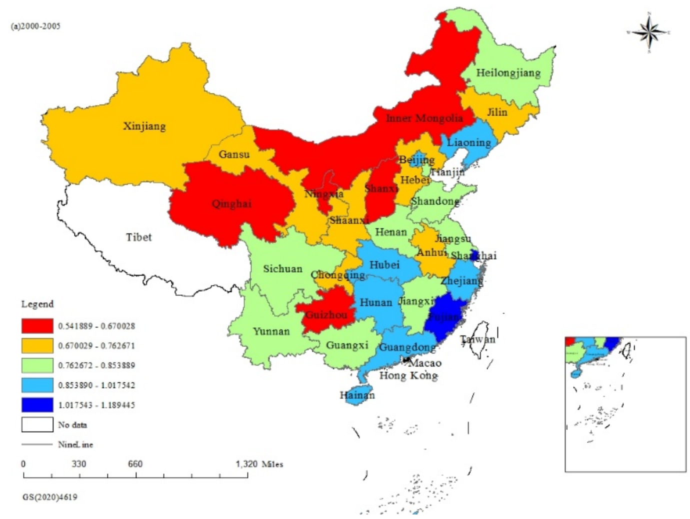
Figure 2. Trends of carbon emissions in China and its three major regions

The country was further divided into eastern, central and western regions. Figure 2 shows the trends of carbon emission efficiency in the whole country, eastern region, central region and western region during the sample period.

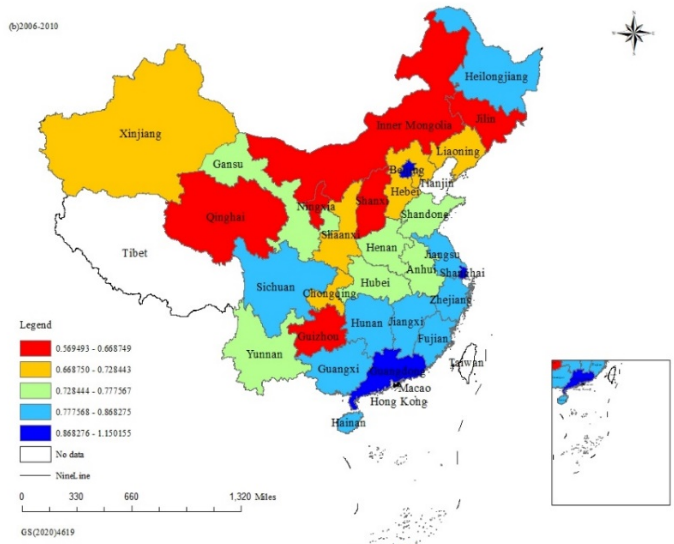
From the trend of carbon emission efficiency, the carbon emission efficiency in the whole country, eastern region, central region and western region changed rather consistently. With the passage of time, the carbon emission efficiency of the three major regions showed a gradual downward trend in the study period. Besides, there were significant differences in carbon emission efficiency between the eastern, central and western regions. As for the mean carbon emission efficiency nationwide, the value was merely 0.7374 in the sample period. Overall, the country performed generally in carbon emission efficiency. There was some distance from the optimal frontier, leaving a great room for improvement.

When it comes to specific regions, the mean carbon emission efficiency of the eastern region, the central region and the western region during the sample period was 0.8326, 0.7276, and 0.6459, in turn. It can be seen that the carbon emission efficiency in the eastern region was higher than the national average. That of the central region was comparable to that of the whole country, with a very small difference. That of the western region was significantly lower than the national average. To sum up, the carbon emission efficiency was high in economically developed regions, and low in less developed regions. This confirms the environmental Kuznets curve theory: in the early stage of economic underdevelopment, environmental pollution is positively correlated with per capita GDP; when the economy enters the developed stage after crossing a certain threshold, environmental pollution and per capita GDP have a negative correlation.

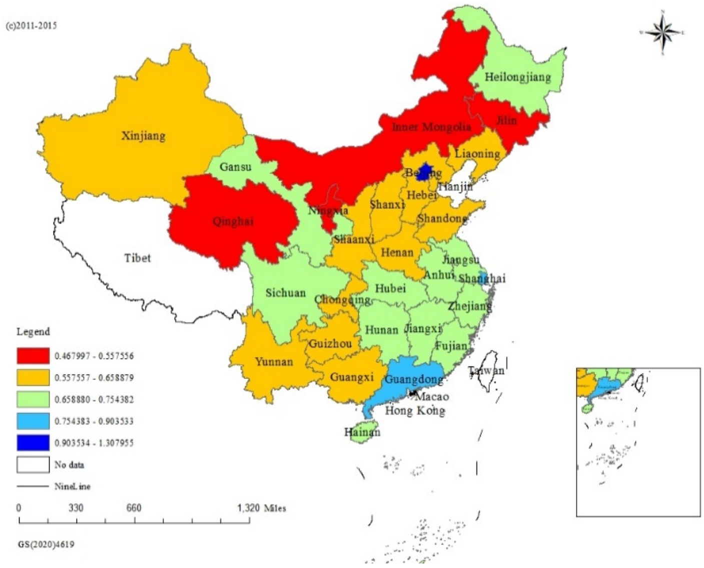
3.1.2 Spatiotemporal variation of carbon emission efficiency



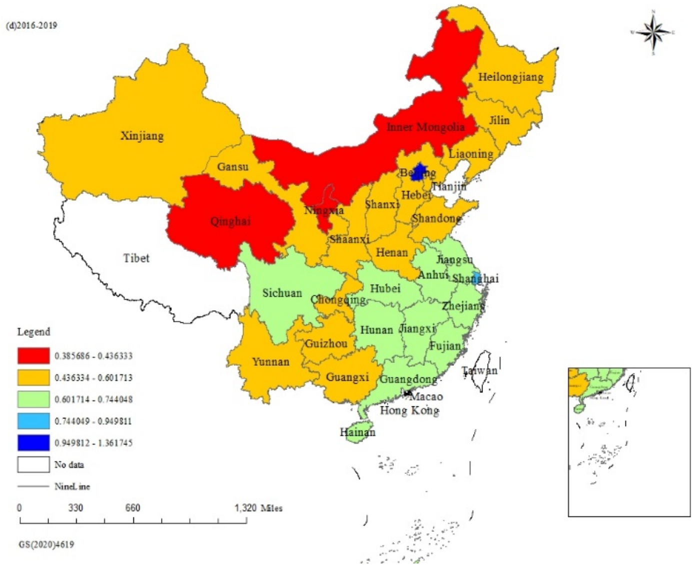
(a) 2000-2005



(b) 2006-2010



(c) 2011-2015



(d) 2016-2019

Figure 3. Spatial distribution of carbon dioxide emission in each province in different periods

To further demonstrate the spatial distribution of carbon emission efficiency in different provinces, this paper divides the study period into 4 periods, namely, 2000-2005, 2006-2010, 2011-2015 and 2016-2019, and obtains the spatial distribution of carbon emission efficiency in 2000-2019 (Figure 3). The carbon emission efficiency was divided into five levels from low to high, and marked by different colors. On the whole, the carbon emission efficiency showed a big difference between the eastern, central and western regions. The provinces with high efficiency were mainly concentrated in the eastern region, while the provinces with low efficiency are mostly in the central and western regions.

In the eastern region, the carbon emission efficiency of Beijing, Shanghai and Guangdong remained at a high level over the years. It can be said that these three provinces are the most economically developed regions in China. Their good performance in carbon emission reduction is associated with their advanced industrial structure, and high enterprise production technology. Zhejiang, Jiangsu and Fujian performed well in the early stage, but their carbon emission efficiency declined in the later stage. Hence, these provinces fail to continuously strengthen carbon emission reduction in the process of economic development. Their carbon emission efficiency has not increased but decreased.

In the central and western regions, the carbon emission efficiency of most provinces mainly belonged to the fourth and fifth levels (low efficiency). In the initial stage, Hubei, Hunan, Sichuan, and Jiangxi were the only provinces in these regions to perform satisfactorily in carbon emission efficiency. In particular, the carbon emission efficiency of Inner Mongolia, Qinghai and Ningxia lingered on the lowest, fifth level throughout the study period. From the perspective of time evolution, only Guizhou and Shanxi managed to improve carbon emission efficiency, while the other provinces witnessed a fall in carbon emission efficiency.

Except for a few provinces along the eastern coast, most provinces in China had a relatively low carbon emission efficiency. With the passage of time, only a few provinces managed to improve carbon emission efficiency, while most provinces encountered a decline in the efficiency. Therefore, China faces an arduous task of energy conservation and emission reduction, and needs to cut carbon emissions significantly in the future.

3.2 Results of Tobit Regression

The influence of environmental regulation and technological progress on carbon emission efficiency was estimated by the Tobit model on Stata 12.0. The results are displayed in Table 2.

Environmental regulation has a positive effect on carbon emission efficiency at the 1% significance level. This result supports the expectation that environmental regulation forces enterprises to reduce emissions. China is vigorously promoting carbon peaking and carbon neutrality, and stepping up environmental regulation. As mentioned previously, the Chinese government has perfected the policies on taxes and pollution fees, which gradually increase the cost burden of enterprises using fossil energy. The supply and demand of fossil energy are thus decreased, contributing to carbon reduction. Moreover, the government implemented measures like raising exhaust emission standards and shutting down some high-consumption and high-pollution enterprises. These measures also contribute to energy conservation and emission reduction. As founded by Zhang et al. (2020), stricter environmental regulation is more effective in reducing carbon emissions.

Technological progress has a significant positive correlation with carbon emission efficiency. This finding is consistent with the previous expectation. The results show that increasing the proportion of internal R&D expenditure to GDP helps to improve carbon emission efficiency. Ma et al. (2011) found that higher R&D spending can effectively reduce carbon dioxide emissions, thereby promoting China's carbon reduction agenda. In a recent study of OECD countries, Petrović & Lobanov (2020) also discovered that higher R&D investment reduces the growth of carbon dioxide emissions, and promoted the consumption of clean energy. At present, the Chinese government realizes that scientific and technological innovation is the only way to achieve carbon peaking and carbon neutrality. Therefore, China has increased investment in R&D, and thus continuously improved technological innovation. According to the *2021 Statistical Bulletin of National Science and Technology Funding Investment*, China diverted 181.7 billion yuan to basic research in 2020, an increase of 23.9% compared with 2019. In addition, the total R&D expenditure increased rapidly from 2011 to 2020 at an annual growth rate of 12.2%. In short, technological progress has become the main measure to promote regional energy conservation and emission reduction, which will undoubtedly improve carbon emission efficiency.

The estimated coefficient of the cross term between environmental regulation and technological progress was negative, passing the test at the 1% significance level. This means the lack of good interaction between environmental regulation and technological progress. The carbon emission efficiency is thereby inhibited. The possible reason is that, the rising environmental regulation in China suppresses corporate R&D activities more and more obviously. Under high environmental regulation, enterprises are forced to purchase pollution control equipment, resulting in an increase in production costs. The R&D investment of enterprises is thence squeezed, and their market competitiveness is weakened, leading to a fall in output (Yuan et al., 2017). At the same time, environmental regulation induces a large cost pressure in resource-intensive industries (Conrad & Wastl, 1995). This idea has been proved by many scholars. Tang et al. (2020) explored 496 A-share industrial enterprises in China from 2002 to 2017, and found that environmental regulation suppresses the innovation efficiency of enterprises in the short term. Liu et al. (2020) analyzed an economic zone in the Yangtze River Basin, and discovered that inappropriate regulation will reduce the marginal efficiency of green technology innovation.

Table 2. Regression results of Tobit model

Variable	Coefficient	T-value	P-value
ER	0.0008^{***}	3.36	0.001
TP	11.5906^{***}	11.74	0.000
*TP*ES*	-0.0880^{***}	-4.85	0.000
IS	-0.1844^{**}	-2.32	0.021
FD	-0.0944^{***}	-5.34	0.000
OU	2.7390^{***}	10.06	0.000
ES	-0.34840^{***}	-8.79	0.000
UL	-0.4746^{***}	-8.49	0.000
L- likelihood		424.4963	

Note: *, ** and *** are the significance levels of 10%, 5%, and 1%, respectively.

Concerning the impact of other control variables on emission efficiency, the impact of industrial structure on carbon emission efficiency was negative at the 5% significant level. The higher the proportion of the output value of the secondary industry in GDP, the more unfavorable it is to carbon emission efficiency. Thus, optimizing and upgrading the industrial structure is a reasonable measure to increase carbon emission intensity (Cheng et al., 2018). Carbon emission reduction can be realized by reducing the proportion of the traditional secondary industry and vigorously developing the tertiary industry, which promotes clean production and optimizing the distribution of factors.

Financial development has a significant negative correlation with carbon emission efficiency. The possible reason is that financial development supports regional economic growth, leading to an increase in carbon emissions. Zhang (2011) confirmed that financial development significantly increases China's carbon dioxide emissions.

Opening-up plays a significant role in promoting carbon emission efficiency. This result supports the pollution halo hypothesis: the introduction of FDI by the host country results in technological spillover, which enhances local regional environmental governance (He, 2006).

Energy structure has a negative impact on carbon emission efficiency at the 1% significance level. That is, the higher the proportion of coal consumption in total energy consumption, the more difficulty it is to improve carbon emission efficiency. Dependent on energy endowment, fossil fuel still accounts for a large part of the energy consumption structure in China. The over-reliance on fossil fuel will limit the effectiveness of carbon emission reduction measures (Sun & Huang, 2020).

Urbanization level (UL) significantly inhibits the improvement of carbon emission efficiency. This means urbanization hinders the achievement of carbon reduction targets, because it increases energy demand. Wang et al. (2016), and Xu et al. (2018) also proved that urbanization is an important reason for accelerating the growth of carbon emissions.

4. Conclusions

Taking carbon emission as the bad output, this study constructs an index system for carbon emission efficiency. On this basis, the 30 Chinese provinces in 2000-2019 were selected as the objects, and the carbon emission efficiency of each province was measured by the Super-SBM model. In addition, the Tobit model was adopted to analyze how the efficiency was affected by environmental regulation, technological progress, and the interaction between the two factors. The main conclusions are as follows:

(1) During the sample period, China's carbon emission efficiency presents a large inter-provincial difference. Only a few provinces like Shanghai and Beijing reached the efficient frontier, while all the other provinces failed to do so. Overall, the high efficiency provinces cluster in the developed coastal regions, while most inland provinces fail to achieve a satisfactory efficiency.

(2) By dividing China into three regions, it could be seen that the three regions all had a slowly falling carbon emission efficiency in the sample period. Besides, they diverged clearly in that efficiency. The eastern region had the highest carbon emission efficiency, followed in turn by the central region and the western region.

(3) According to the spatiotemporal variation of carbon emission efficiency, most eastern provinces had a satisfactory carbon emission efficiency, but the efficiency declined with the passage of time. Most provinces in the central and western regions had a large potential for improving their carbon emission efficiency. As time passed away, the efficiency only improved in a few of these provinces, while fell to different degrees in most provinces.

(4) The results of the Tobit model show that both environmental regulation and technological progress both significantly promoted carbon emission efficiency, but their cross term clearly suppressed carbon emission efficiency. When it comes to the control variables, carbon emission efficiency has a significantly positive relationship with opening-up, and a significantly negative relationship with industrial structure, financial development, energy structure, and urbanization level.

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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