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The Impact of the Carbon Emission Trading Shadow Price on the Green Total Factor Productivity of the Power Industry in China

Longtian Zhang * and **Zheng Pan**

School of Economics and Management, China University of Petroleum-Beijing, Beijing 102249, China
* Correspondence: zhanglongtian@cup.edu.cn; Tel.: +86-13006537498

Abstract: To mitigate the problem of global climate change, governments have taken measures to reduce greenhouse gas emissions. Carbon emission trading has gradually attracted attention as a market-oriented option. Power industry panel data from 30 provinces in China were used for an empirical analysis in this study. The super-efficiency Slack-Based Measure (SBM) model was used to calculate the shadow price of carbon trading and the green total factor productivity (GTFP), and the Ordinary Least Squares (OLS) regression model was used to quantitatively analyze the correlation between the shadow price of carbon trading and the GTFP of the power industry. The results showed that the shadow price of carbon trading had a significantly negative impact on the GTFP of the power industry; therefore, it needs to be improved and perfected. Through a further analysis using the heterogeneity test, it was found that there were problems in the current carbon trading price mechanism. In the face of the above problems, we offer suggestions for improvement from the perspectives of the government and companies. This study helps deepen the understanding of carbon trading prices and the GTFP in the power industry, and it provides a reference for formulating more effective carbon trading policies and corporate green management strategies.

Keywords: carbon emission trading; shadow price; green total factor productivity; electric power industry

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1. Introduction

In recent years, the problem of global climate change has become increasingly serious, and reducing carbon emissions has become a common goal for governments. It is necessary to promote green and low-carbon development among economic market entities [1]. Emission trading is a market-based regulatory tool recognized by academia, which internalizes carbon emissions as a cost or tradable resource for businesses.

In July 2021, China's carbon emission trading market was officially launched on the Shanghai Environmental Energy Exchange. The total trading volume on the first day of transactions was 4.104 million tons, with a total turnover of CNY 210,230,100. This market covers high-carbon industries, such as the electricity, steel, cement, and aluminum industries, and has resulted in China becoming the world's largest carbon emission trading market, in which the power industry is an important participant. As China's largest carbon emission industry, its development in China's carbon emission trading market has attracted much attention. According to data from the relevant agencies, by the beginning of 2022, China's power industry had accumulated trading carbon quotas totaling more than 300 million tons, accounting for nearly 90% of the total trading volume. In order to encourage electric power companies to reduce carbon emissions and promote green development, governments have adopted a variety of policy measures, including carbon emission trading systems.

The carbon emission quota of China's power industry is allocated according to its power output. Companies need to buy enough of a quota to cover their carbon emissions. If they exceed their quota, they need to buy more from the market. This has prompted the power industry to strengthen its energy conservation and emission reduction, while also providing it with economic incentives to encourage the use of cleaner energy. Of the many industrial sectors in China, only the power-generation industry has set up a cross-provincial trading market; hence, the carbon emission trading mechanism of the power industry is more mature, and the data are more comprehensive. Green transformation and the development of the power industry are two important tasks involved in China's industrial transformation and upgrading. Therefore, it is necessary to explore the impact of carbon emission prices on the green total factor productivity (GTFP) of the power industry, which has important theoretical and practical significance for guiding the development of China's carbon emission trading market.

The purpose of this study was to explore the causal relationship between the shadow price of carbon emissions and the GTFP of China's power industry. This article emphasizes the importance of carbon trading, provides empirical evidence for exploring the impact of shadow prices of carbon emissions on the GTFP of the power industry, and offers policy recommendations for improving the effectiveness of China's carbon emission trading system. The shadow prices reflect the cost to companies of reducing emissions. The GTFP comprehensively considers the environmental and economic benefits of the enterprise. Therefore, if the shadow price is too high, the cost of reducing emissions for enterprises will be higher, which is not conducive to improving the GTFP of enterprises. The carbon trading pilot, as a market-oriented environmental regulatory tool, can convert carbon emissions and carbon emission rights into costs and benefits for enterprises. Therefore, this study suggests that, in the environment of carbon trading, high shadow prices will harm the GTFP of enterprises. The innovation of this article mainly lies in the following two points. (1) Taking the power industry as the research object, this study investigates the impact of shadow prices on the GTFP. Previous studies have not considered the power industry as an important research object when studying the GTFP. (2) This study uses shadow prices as real prices to reveal the shortcomings of the carbon trading market. At present, the construction of China's carbon trading market is still in its early stages. Therefore, using shadow prices as a true price to reveal the shortcomings of the carbon trading market is of great significance.

2. Carbon Trading Market

In 2011, the Chinese government launched a carbon trading pilot project in Beijing, Shanghai, Tianjin, and Chongqing. In 2013, China expanded the carbon trading pilot to seven provinces and gradually adjusted the trading rules and regulatory mechanisms. As of 2023, China has established carbon trading markets in 31 provinces and regions, and China's carbon market has become one of the world's largest carbon markets.

Figures 1–3 are based on information from the China Carbon Trading website (http://www.tanpaifang.com/). As shown in Figure 1, the turnover exhibited an increasing trend in 2015–2020. In 2016, it increased by 43.7% over 2015, and it increased by 12.9% in 2017. In 2018, it decreased but remained higher than that in 2016. In 2019 and 2020, the turnover significantly increased again, by 23.8% and 33.5%, respectively. In 2020, it was more than 2.5 times that of 2015. In summary, based on the current development trend in the trading volume of China's carbon trading market, there is still room for improvement.

As shown in Figure 2, Guangdong's and Hubei's carbon trading volumes were the top two among all pilot cities; both exceeded 70 million tons, which was much higher than that of the other provinces. In addition, Beijing's, Shanghai's, and Tianjin's carbon trading volumes ranked third, fourth, and fifth, respectively, with values of 14,614,500 tons, 17,396,900 tons, and 9,201,100 tons. Chongqing's and Fujian's carbon trading volumes were relatively small, with 8,690,000 tons and 8,469,800 tons, respectively.

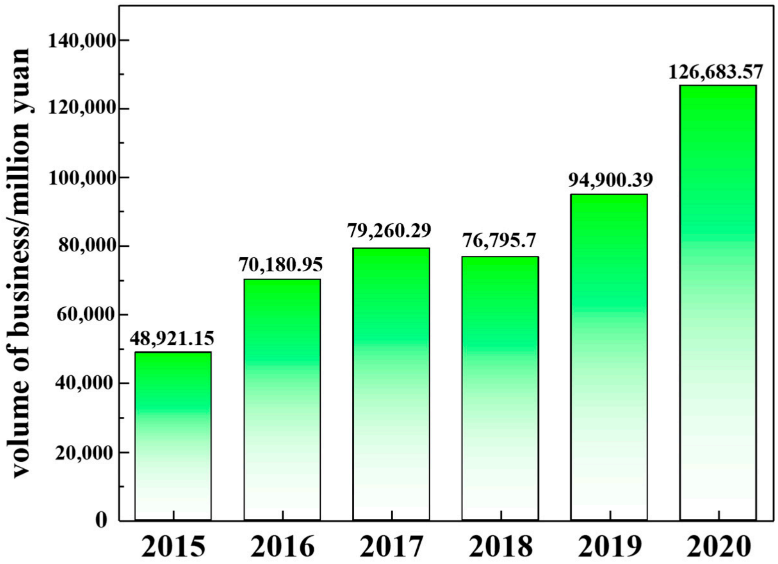

Figure 1. Carbon transaction volume of China's carbon trading market from 2015 to 2020.

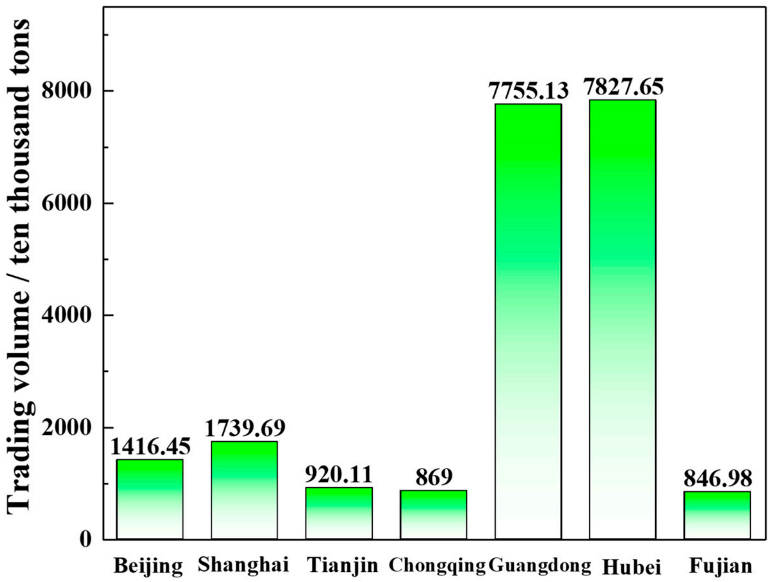

Figure 2. Volume of carbon trading in China's pilot regions as of early 2021.

As shown in Figure 3, the carbon trading prices in different regions were quite different. Beijing had the highest average price, followed by Shanghai and Chongqing. The prices for Hubei, Guangdong, and Tianjin were relatively low. The price for Fujian after 2018 was in the middle of the pilot areas. In addition, the annual average price in these regions fluctuated. From 2015 to 2017, the price of carbon trading was generally low, but in 2018 and 2019, with a reduction in the carbon emission quotas, the price of carbon trading increased everywhere. Among them, the prices for Hubei, Shanghai, and Beijing reached the highest point over the six years in 2019, while the prices for other regions, such as Guangdong and Fujian, increased significantly in 2019. The annual average price of these carbon trading pilot areas reflects the development of China's carbon emission trading market, and it also shows that there are differences in the participation and performance of different regions in the carbon market.

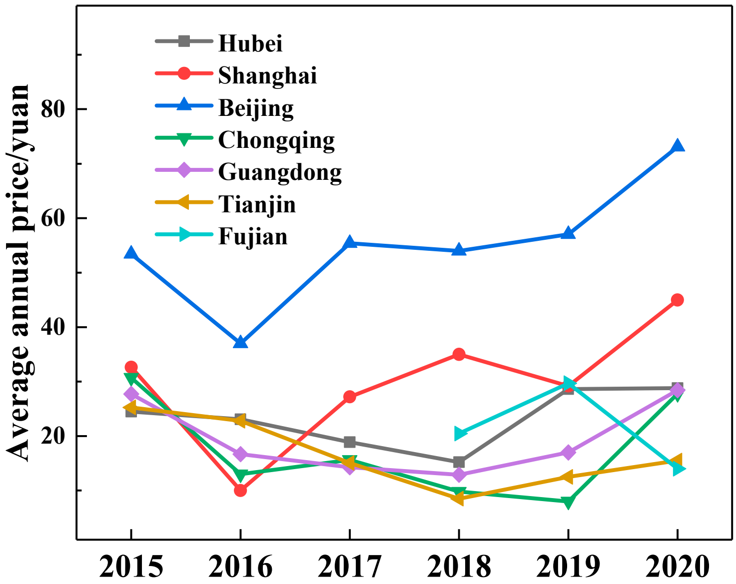

Figure 3. Annual price of carbon trading in seven pilot carbon trading regions.

It can be seen that (1) yearly growth is evident in the carbon emission trading volume; (2) marked regional disparities exist in trading volumes; and (3) carbon trading prices show substantial fluctuations with notable regional variations. These data suggest that the construction of China's carbon emission trading market is in its early stages and immature.

3. Literature Review

The literature review of this paper mainly includes three aspects: carbon trading price research, GTFP research, and the research on the impact of carbon trading prices on the GTFP.

3.1. Carbon Trading Price Research

The research on carbon trading prices mainly includes the influencing factors and price forecasts. Keppler et al. [2] found that the carbon price of the first stage of the EU carbon emission market is guided by the long-term emission reduction cost, and an increase in the coal and natural gas prices will increase the emission reduction cost for companies, thus significantly pushing up the price of carbon emission rights. In the second stage, the carbon price is more driven by the electricity price, and the short-term rent-seeking phenomenon is obvious. Aatola et al. [3] added stock parameters when describing the economic situation. Zhao et al. [4] found that market factors and policy factors have an impact on the carbon price, among which market factors have the greatest impact. Jiang et al. [5] used a multiple regression model and found that carbon trading prices are significantly correlated with financial markets, energy prices, and air quality. Wang et al. [6] demonstrated that energy prices, the GDP growth rate, temperature, and precipitation have varying degrees of impact on the carbon prices. Li [7] found that natural gas prices, crude oil prices, and the macroeconomy have a positive impact on the pricing of carbon emission trading, while coal prices have a negative impact.

Benz and Truck [8] used the GARCH model and the Markov state transition model to predict the carbon emission trading price fluctuations and found that the Markov state transition model had a better prediction accuracy than the GARCH model. Seifert et al. [9] proposed a stochastic equilibrium model based on the characteristics of the EU carbon emission trading market that is suitable for predicting the fluctuations in carbon spot trading prices. Eugenia Sanin et al. [10] achieved better modeling results by combining the time-varying jump probability function with the ARMA-GARCH model to conduct an empirical analysis of the EU carbon emission trading market price. In order to solve the problem of ARMA model selection, Wang [11] used a boosting algorithm to find the optimal subset of ARMA; the boosting–ARMA model had a higher carbon trading price prediction accuracy and was very convenient and fast. Ji et al. [12] used the carbon trading price for the pilot areas of Guangdong, China, as the research object and established a ternary linear regression model to predict the carbon trading price. They achieved ideal results using this model. Yin et al. [13] constructed the 'China carbon trading price index', and then a SVAR model with the China carbon trading price index, the EU carbon trading price index, an industrial index, the China Securities Index energy index (CSI), an air quality index (AQI), and the HS300 to study carbon trading prices in China. Pradhan et al. [14] used country-specific dynamic computable general equilibrium (CGE) models. This paper estimated carbon prices in China and India, and compared the effects of carbon pricing policies under terms of trade effects.

The existing literature mainly focuses on predicting carbon trading prices, emphasizing the differences between different factors and models. However, the construction of China's carbon trading market is still in its early stages, and the prices of carbon trading may be extremely unstable, even distorted, and cannot reflect true price information. Therefore, when studying China's carbon market, full consideration should be given to the immaturity of this market.

3.2. Green Total Factor Productivity Research

The research on the GTFP is mainly divided into influencing factors and measurement methods. Shi et al. [15] used the GTFP to measure the quality of economic development and evaluated the level of green financial development from multiple dimensions, such as green credit and green investments. The environmental Kuznets curve theory concerns the relationship between the level of economic development and environmental pollution. It is generally believed that the relationship between the two shows an inverted U-shaped curve. According to Zheng et al. [16], the relationship between China's carbon emissions and economic growth is long-term, steady, and shows an inverted U-shape. Zhao et al. [17] introduced a multi-participation environmental governance system as a regulating variable in their empirical analysis and found that, in the environmental governance system, multi-participation subjects can realize an adjustment in the steepness level of the environmental Kuznets curve and the location of the inflection point, which produces the dual effects of "peak decline" and "inflection point decline". Zhao et al. [18] aimed to assess the level of smart transportation technology, and then investigate its impact on green total factor productivity using the instrumental variable–generalized method of moments (IV-GMM) model.

More and more scholars have noticed the impact of environmental regulation on the GTFP [19,20]. Li et al. [21] found that environmental regulation has a regional impact on the GTFP. Yuan [22] determined that this impact is also applicable in the industrial sector. Urbanization promotes GTFP growth and economic growth through the role of "scale externalities" [23,24]. On the other hand, urbanization will cause population and economic activities to gather to a certain extent and generate an external economy [25], so that resources such as capital and technology are better allocated, thereby promoting TFP growth [26,27]. Zheng [28] found that urbanization significantly promoted the growth of the GTFP.

The current measurement methods for the GTFP index mainly include the parametric method, the semi-parametric method, and the non-parametric method. The commonly used parametric methods include the Solow residual method and the stochastic frontier function method (SFA). The Solow residual method calculates the total factor productivity by deducting the growth rate of all the input factors; however, this method is difficult to implement in real life. Zhao et al. [29] found that China's labor factor elasticity and capital factor elasticity are changing, which is inconsistent with the fixed-elasticity hypothesis of the Solow residual value. The stochastic frontier method was first proposed by Aigner [30] et al. in 1997, which effectively eliminated the influence of random errors. Yu et al. [23] found that the degree of marketization, the innovation investment, and the enterprise size have a positive impact on the total factor productivity of China's high-tech industry, and the degree of influence is different in different regions. The semi-parametric method mainly includes two types: the OP semi-parametric method proposed by Olley and Pakes [31] and the LP semi-parametric method proposed by Levinsohn and Petrin. These methods are mainly applied to measure the total factor productivity at the micro-enterprise level. Many of the parametric and non-parametric methods have been optimized. For example, Blundell and Bond [32] effectively solved the endogenous problem in regression by adding instrumental variables to the GMM (generalized method of moments) estimation of the TFP. In the non-parametric method, a data envelopment analysis (DEA), which is suitable for "multi-input–multi-output" situations, is the most widely used. The traditional DEA method uses the direction distance function (SDF) to calculate the total factor productivity. One of the assumptions of this method is that the output changes in the same proportion. However, when calculating the GTFP index, the expected output increases while the undesired output decreases. In order to solve this problem, Fare et al. [33] combined the DEA method with the Malmquist index. On this basis, Chung et al. [34] used the Malmquist–Luenberger index method to consider the undesired output and calculate the GTFP index. Chen [35] showed that the slack-based measure (SBM) model is also widely used in efficiency evaluation.

The research in the existing literature mainly discusses the impact of environmental regulations, urbanization, marketization, and other factors on the GTFP. It is worth noting that shadow prices, as an important reflection of a company's ability to reduce emissions, have been overlooked by such research. Shadow prices reflect the number of products a company reduces for every one unit of pollution. Therefore, studying shadow prices and the GTFP is of great significance.

3.3. Research on the Impact of Carbon Trading Prices on the GTFP

Wang et al. [36] calculated the GTFP growth rate of each province in China and empirically analyzed its influencing factors. The results showed that the growth rate in each region is steadily increasing, and China's economic growth is gradually transforming from factor inputs such as capital, labor, energy, and environmental capacity (represented by CO_2 emissions) to sustainable GTFP. Liu [37] studied the impact of carbon trading on green performance from the perspective of Chinese industrial companies and found that carbon trading also has a positive impact on the performance and profitability of companies. Song et al. [38] found that carbon trading policies have a positive effect on promoting corporate environmental investments and improving green performance. Through an empirical study of Chinese companies, Wan et al. [39] found that a carbon trading policy can promote the green technology innovations and environmental management ability of companies, thus improving their performance and profitability. Meng et al. [40] studied the impact of a carbon trading policy on carbon emissions and the economic performance of China's industrial sector by collecting relevant data on Chinese industrial companies and using panel data analysis methods. A carbon trading policy can promote a reduction in carbon emissions and improve the economic benefits in China's industrial sector. Zhang et al. [41] used the data for pilot provinces and cities to analyze the impact mechanism of carbon trading on the carbon peak and carbon neutralization. Zhang [42] used the data for some provinces and cities in China to analyze the impact of carbon trading on the economy and the environment. Xiao et al. [43] provided firm-level evidence of TFP improvement from China's pilot of carbon trading. Zhou et al. [44] studied the direct impact and mechanism assessment of carbon emission trading policy on the GTFP, finding that carbon emission trading policies have a positive impact on the GTFP.

Considering the immaturity of China's carbon market, another concern is that the actual carbon trading prices may be distorted and may contain too many confounding factors. Therefore, it is necessary to study the total factor productivity through shadow prices. The existing literature includes important research on carbon trading prices, the green total factor productivity, and their relationship. However, there is still a certain research gap. (1) From the perspective of the shadow prices of carbon emissions, studying the GTFP has been overlooked. Although there are direct trading prices, shadow prices can better reflect the "true price", especially for an immature trading market. (2) In the literature, few studies have focused on the power production industry. As the largest carbon-emitting industry in China, the power industry is an important participant in the carbon trading market. This study aimed to examine the impact of carbon emission shadow prices on the GTFP of the power industry and reveal the differences between carbon trading pilot areas and non-pilot areas. This study also provides suggestions for the design of carbon trading markets and the green and low-carbon transformation of the power industry.

4. Methodology

4.1. Measurement of Shadow Price Calculation Method in Power Industry

4.1.1. Shadow Price Based on SBM Dual Model

Shadow prices express by how much the output must be reduced if an industry wants to reduce their carbon emissions by one unit. By referring to Zhang et al. [45], this article used the SBM dual model to calculate shadow prices. S_1 is the number of good outputs. S_2 is the number of undesirable outputs. M is the number of inputs. x_0, y_0, b_0 represent the row vector $(x_0, \ldots x_{M0})$, $(y_0, \ldots y_{S10})$, $(b_0, \ldots b_{S20})$. μ_y, μ_b, ν are the dual-variable of the good outputs, bad outputs, and inputs, respectively. See the following equation.

$$\text{Max p} = \mu_y y_0 - \nu x_0 - \mu_b b_0$$

$$\text{s.t.p} \leq 0$$

$$v \geq \frac{1}{M} * 1/x_0$$

$$\mu_y \geq \frac{1+p}{S_1+S_2} * 1/y_0$$

$$\mu_b \geq \frac{1+p}{S_1+S_2} * 1/b_0$$

Based on the calculation results of the above equation, the shadow price of carbon emissions can be expressed by the following equation.

$$cp = \mu_b/\mu_y$$

4.1.2. Variable Selection and Data Sources

In this study, labor (L), energy (E), and stock (K) were selected as the input factors, and the gross domestic product (GDP) and CO_2 were selected as the expected output and undesired output, respectively. L was calculated based on the number of employed individuals. The capital stock (K) was calculated by using the perpetual inventory method based on the data for the total fixed-asset investments. The depreciation rate was 9.6%, and the capital stock in the base period was 10% of the fixed capital investments in the base period. E was uniformly converted into standard coal based on various energy-consumption levels. The GDP was converted into the actual regional gross domestic product using the base period as a constant price.

The data needed for these calculations were obtained mainly from the *China Statistical Yearbook*, *China Urban Statistical Yearbook*, *China Urban Construction Statistical Yearbook*, *China Regional Statistical Yearbook*, and *China Energy Statistical Yearbook*. When calculating the level of labor force, the data for the urban non-agricultural population were mainly obtained from the *China Population and Employment Statistical Yearbook*. Carbon dioxide emissions were mainly estimated using the IPCC calculation method, namely, the emission factor method. The CO_2 data were obtained from the China Carbon Accounting Database (https://www.ceads.net.cn/, accessed on 7 April 2024).

In view of the availability of data, the period 2016–2020 was selected as the research interval, and the panel data of 30 provinces in China were selected as the sample.

4.2. Measurement of Green Total Factor Productivity Index in Power Industry

4.2.1. The GTFP Based on Super SBM Model

This article uses the Super SBM model to evaluate the efficiency of each unit. The Super SBM model is currently a classic model in data envelopment analysis and is widely recognized by academia. (1) The SBM model has non radial characteristics. The general DEA models such as CCR (Charnes–Cooper–Rhodes) and BCC (Banker–Charnes–Cooper) assume that the reduction in input or the increase in output follow the principle of proportionality. On the one hand, this principle of proportionality is inconsistent with reality. On the other hand, it may overestimate the efficiency value and lack guidance for reality. Therefore, this article adopts the SBM model for measurement, which can identify the redundancy of inputs to the maximum extent. (2) The DEA model is a frontier measurement method with efficiency values ranging from 0 to 1. An efficiency value of 1 indicates that the decision-making unit is technically effective. Effective technology does not necessarily mean that there is no need for comparison and improvement. This article adopts the super efficient processing method to further distinguish technically effective units.

It was assumed that there are M types of inputs, where m represents the type of input, S_1 the type of good output, and S_2 the type of bad output. Good output is the expected output in the production process, which means more is better, such as products. Bad output is an unexpected output in the production process that means less is better, such as pollutants. X represents the input vector, Y represents the output vector, and B represents the bad output vector. λ stands for intensity variables. x_{m0}, y_{s_10}, and b_{s_20} are the input, good output, and bad output variables of the measured units. s_{mo}^-, $s_{s_10}^+$, and $s_{s_20}^+$ are slack variables for input, good output, and bad output, respectively. The planning formula for the Super SBM model is as follows.

$$\rho^* = min\frac{1-\frac{1}{M}\sum_{m=1}^{M} s_{mo}^-/x_{m0}}{1+\frac{1}{s_1+s_2}\left(\sum_{s_1=1}^{s_1} s_{s_10}^+/y_{s_10}+\sum_{s_2=1}^{s_2} s_{s_20}^-/b_{s_20}\right)}$$

$$\mathrm{s.t.x_{m0}} = \mathrm{X}\lambda + \mathrm{s_{n0}^-}, \mathrm{m} = 1...\mathrm{M};$$

$$\mathrm{y_{s_10}} = \mathrm{Y}\lambda - \mathrm{s_{s_10}^+}, \mathrm{s_1} = 1...\mathrm{s_1};$$

$$\mathrm{b_{s_20}} = \mathrm{B}\lambda + \mathrm{s_{s_20}^-}, \mathrm{s_2} = 1...\mathrm{s_2};$$

$$s_m^- \geq 0,\ s_{s_1}^+ \geq 0,\ s_{s_2}^- \geq 0,\ \lambda \geq 0$$

4.2.2. Variable Selection and Data Sources

To determine the GTFP of the power industry, the commonly used variables are L, K, E, Y1, and Y2. The labor input (L) refers to the amount of all types of labor used for production in an enterprise, including employees and managers. The labor input (L) refers to the number of all labor used for production in an enterprise, including employees and managers. The capital stock (K) refers to the quantity and value of various production materials and equipment used by companies for production. The energy input (E) refers to the coal energy used in the production process of the power industry. Yield 1 (Y1) usually refers to the main output of the power industry: power generation. Yield 2 (Y2) refers to CO_2 emission.

This study took the relevant data for the power industry from 2016 to 2020 as the research objects and calculated the GTFP of the power industry for 30 provinces. The data for Tibet, Hong Kong, Macao, and Taiwan were not considered, as they were unavailable. L and K were obtained mainly from the *China Energy Statistical Yearbook*. E and Y1 were obtained mainly from the *China Electric Power Statistical Yearbook*. Y2 was obtained mainly from the CEADs database (https://www.ceads.net.cn/, accessed on 7 April 2024).

4.3. Theoretical Framework and Hypotheses

The shadow price of carbon emissions indicates the price that companies need to pay to reduce their carbon dioxide emissions by one unit, which represents the marginal cost of carbon emission reduction. We hypothesize that the shadow price of carbon emissions can inhibit the GTFP of the power industry. Firstly, when the shadow price of carbon is too high, power companies need to pay higher carbon emission costs, which will increase operating costs and financial burdens. Companies may reduce their expenditure on green technology and environmental protection facilities as a result. This may lead to a slowdown in the speed of technology and facility renewal by companies, thus inhibiting the GTFP of the industry. Secondly, the high shadow price of carbon will affect the investment efficiency of the power industry. When power companies invest in green technologies and environmental protection facilities, they may take into account the rate of return and benefits. The operating costs, investment returns, and technical facility update speed of companies may be affected by the shadow price of carbon trading. Therefore, we propose Hypothesis 1.

Hypothesis 1. *A high shadow price can inhibit the GTFP of the power industry.*

Companies in the pilot areas of carbon trading may be more vulnerable to this inhibition, as companies in the carbon trading pilot area are more likely to carry out emission reduction activities, which are vulnerable to the negative impact of high emission reduction costs. First of all, the carbon trading pilot area has a stronger level of environmental regulation, which has prompted companies to carry out environmental governance. In fact, the carbon trading pilot area represents market-based environmental regulation. On the one hand, the government usually supervises and controls the companies in the pilot areas; on the other hand, the promotion and publicity of the carbon trading pilot policy will promote the formation of a social atmosphere and consensus for low-carbon development, in addition to encouraging the public to supervise and vote on companies. Secondly, companies in carbon trading pilot areas are also more aware of the need to reduce carbon emissions in the present and future. The implementation of a carbon trading policy involves carbon emission quotas and carbon emission trading, which directly affect the economic interests and operating costs of companies. In addition to carrying out daily business activities to obtain profits, companies can obtain economic benefits through carbon emission reduction activities. Although emission reduction activities are often detrimental to short-term profits, the anticipation of long-term benefits encourages companies to pursue such activities. To summarize, whether active or passive, companies in carbon trading pilot areas pay more attention to and adopt carbon emission reduction activities. Companies engaged in carbon emission reduction activities are more vulnerable to the negative effects of high shadow prices. Therefore, we propose Hypothesis 2.

Hypothesis 2. *The carbon trading pilot aggravates the inhibition of the shadow price on the GTFP.*

If the high shadow price of carbon can inhibit the green total factor productivity of the power industry, then companies can alleviate this inhibition by improving their emission reduction technology. On the one hand, companies with a high level of technological innovation often belong to the group of low-carbon companies, which are not vulnerable to the negative impact of high emission reduction costs; on the other hand, companies can make up for the losses caused by carbon emissions through technological innovations and by reducing their power-generation energy consumption. First of all, low-carbon and high-tech innovation companies often rely on technological innovations to obtain their profits. Low-carbon companies are not the object of environmental governance and are less affected by government environmental regulations; hence, they are not sensitive to changes in the shadow price of carbon. Therefore, high-tech innovation companies can alleviate the inhibitory effect of the carbon shadow price on their corporate green performance. Second, carbon emission technology innovations can help companies improve their production efficiency and resource utilization efficiency, promote social development and sustainability, enhance their enterprise competitiveness and innovation ability, and strengthen their social responsibility and moral obligation, in order to improve the green total factor productivity performance of the industry. Through technological innovations, companies can reduce their environmental load and carbon emissions; develop environmentally friendly products and services; promote social development and sustainability; improve their production efficiency, product quality, and service level; enhance their competitiveness and innovation ability; and better fulfill their social responsibilities and moral obligations. Therefore, we propose Hypothesis 3.

Hypothesis 3. *Carbon emission technology innovations alleviate the inhibitory effect of the shadow price on the GTFP.*

4.4. Research Model and Variables

4.4.1. Research Model

The OLS method, extensively employed in economic data analysis and modeling, revolves around fitting a linear model by minimizing the sum of squared residuals. We have the GTFP as a dependent variable, cp as an independent variable, and pgdp, expand, and indstr as control variables. There is a linear relationship between them, as follows:

$$\mathrm{GTFP} = \beta_0 + \beta_1\mathrm{cp} + \beta_2\mathrm{pgdp} + \beta_3\mathrm{expand} + \beta_4 indstr + \varepsilon \quad (1)$$

where β_0 represents the intercept, β_1 are the coefficients of the independent variable, and ε is the error term. We mainly focus on the coefficients of β_1, including positivity, negativity, and significance. The goal of OLS is to estimate the parameters of the model by minimizing the sum of squared residuals, as follows:

$$\min\sum \varepsilon_i^2 \quad (2)$$

The hypotheses in this study were tested mainly using a regression method. For Hypothesis 1, we examined the impact of the explanatory variable (the carbon trading shadow price) on the explained variable (the GTFP). If the coefficient is significantly negative, Hypothesis 1 is verified. Hypotheses 2 and 3 were tested using a heterogeneity test, namely, grouping regression. If the inhibition effect of the carbon trading shadow price in the non-carbon trading pilot group is smaller than that in the carbon trading pilot group, Hypothesis 2 is verified. If the inhibition effect of the carbon trading shadow price in the carbon emission technology innovation group is smaller than that in the low-technology innovation group, then Hypothesis 3 is verified.

4.4.2. Variable Selection and Data Sources

This study used the calculated shadow price (cp) of carbon trading for 30 regions of China from 2016 to 2020 as the independent variable and tested the impact of the shadow price on the green total factor productivity in the power industry. The GTFP index of the power industry for 30 regions of China from 2016 to 2020 was used as the dependent variable in the OLS method. In order to increase the accuracy, control variables were added in this study that may have an impact on the green development of electricity, namely, pgdp, expand, indstr.

The specific definitions and sources of variables are shown in Table 1.

Table 1. Specific definitions and sources of variables.

Variable Name	Definition	Type of Variable	Source
cp	Shadow price of carbon trading in the region	Independent variable	This article calculates that
GTFP	Green total factor productivity in the power industry	Dependent variable	This article calculates that
pgdp	GDP per capita in the region	Control variables	*China Statistical Yearbook*
expand	The growth rate of electricity consumption in the region	Control variables	*China Electric Power Statistical Yearbook*
indstr	The level of industrialization in the region	Control variables	*China Statistical Yearbook*

5. Empirical Results

5.1. Shadow Price Calculation Results and Analysis

We substituted the panel data into the production function to obtain an estimation. Then, the actual data for the Y, E, L, and K in each province and region in each year were substituted into the formula. The average shadow prices of carbon emission rights for each province and region were calculated, as shown in Table 2. Finally, the shadow price of the carbon emission rights in the national market were calculated using a weighted average (Figure 4).

Table 2. China's regional carbon shadow price for the period 2016–2020 (Unit: yuan/ton).

Region\Year	2016	2017	2018	2019	2020
Beijing	9397	8135	7669	8534	7447
Tianjin	1818	1762	1465	1164	798
Hebei	1345	1317	1848	1099	1004
Shanxi	759	816	878	689	602
Inner Mongolia	631	521	546	456	392
Liaoning	1193	1193	1485	970	788
Jilin	1177	1116	1085	702	429
Heilongjiang	1390	1319	1421	917	658
Shanghai	6358	4220	4066	4141	6426
Jiangsu	2350	2395	4312	2238	2148
Zhejiang	3160	3008	5049	3029	2965
Anhui	1412	1338	1747	1492	1762
Fujian	2311	2210	2626	2067	2233
Jiangxi	1976	1852	2074	1752	1799
Shandong	1284	1203	2104	951	736
Henan	1437	1436	2559	1550	1755
Hubei	2217	2091	2857	2046	2066
Hunan	2478	2384	3144	2112	1979
Guangdong	3490	3314	10932	3308	3356
Guangxi	1647	1468	1803	1306	1215
Hainan	1253	1299	1113	1288	1335
Chongqing	2413	2276	2362	2399	2580
Sichuan	2720	2799	4310	2776	2880
Guizhou	1123	1085	1255	1128	1199
Yunnan	1744	1590	1751	1534	348
Shanxi	935	927	1124	860	820
Gansu	1254	1240	1292	1164	1144
Qinghai	1546	1461	1080	1361	1386
Ningxia	706	613	416	492	422
Xinjiang	950	908	894	857	852

It can be seen from Figure 4 that the trend in the shadow prices of carbon trading was not stable over these five years. In some areas, such as Jiangsu and Fujian, the prices increased over the five years, and in other areas, such as Beijing and Tianjin, the prices declined. There were also some areas where the prices fluctuated, such as Guangdong and Yunnan. On average, Beijing had the highest and Guangxi had the lowest shadow price of carbon trading over these five years.

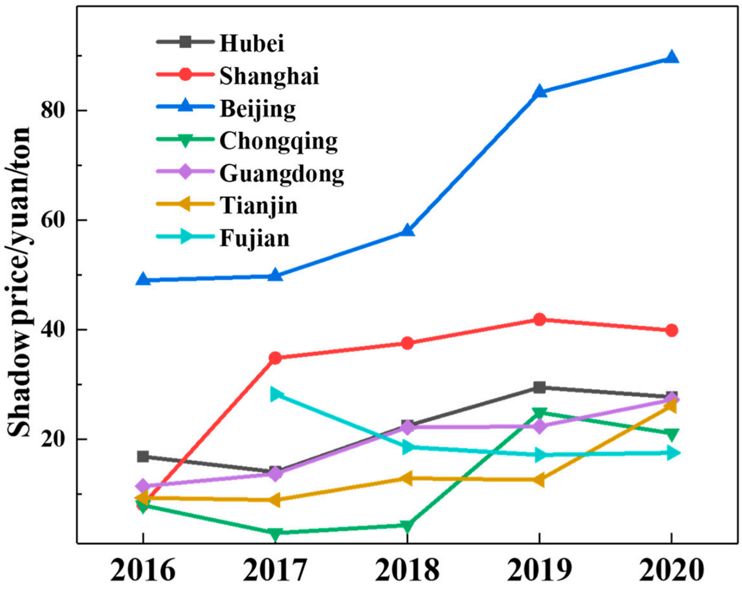

Figure 4. Shadow price of carbon trading in pilot areas of China from 2016 to 2020.

There were obvious regional differences in the shadow price of carbon trading in various regions of the country. Taking 2019 as an example, the prices in Beijing, Shanghai, Guangdong, and other places were relatively high, while the prices in Shandong, Henan, Guizhou, and other places were relatively low. At the same time, we also found that the price differences between regions changed in different years. For example, the shadow price of carbon trading in Guangdong soared in 2018 and fell slightly in 2020. In addition, the median of the carbon trading shadow price in all the regions of the country was below 2000 CNY/ton; however, the price difference between regions was large. Taking 2019 as an example, the median shadow price of carbon trading in Shandong, Anhui, Henan, and other places was only about 1000 CNY/ton, while the median in Guangdong, Shanghai, Zhejiang, and other places exceeded 4000 CNY/ton.

From 2016 to 2020, the average shadow prices of carbon trading for various regions of the country were different. The highest was for Guangdong Province, with an average of 5280 CNY/ton, and the lowest was for Inner Mongolia, with an average of 509.2 CNY/ton. In summary, the national average carbon trading shadow price showed an upward trend from 2016 to 2018 and then declined. The trend in the shadow price of carbon trading in different regions was not the same; however, the overall trend rose.

5.2. GTFP Calculation Results and Analysis

The calculation results are shown in Table 3 and Figures 5 and 6.

From the perspective of the time dimension, the GTFP values in different regions fluctuated greatly between years, and there were no obvious upward or downward trends overall. From the perspective of the spatial dimension, the GTFP values of different regions were quite different. The GTFP value of Fujian Province was the highest, while the GTFP value of Beijing was the lowest. The order from first to seventh was Fujian Province, Shanghai City, Hubei Province, Guangdong Province, Tianjin City, Chongqing City, and Beijing City. Because the GTFP is an indicator of the total factor productivity, the productivity and technical level of these areas were relatively high; however, the specific reasons for the above phenomenon may involve various factors, such as the industrial structure, natural resources, and human resources. The GTFP in Beijing was relatively low between 2016 and 2020. A possible reason for this is that most companies in this region are at the middle and high ends of the industrial chain and lack downstream production links, which means that their industrial chain is incomplete and lacks industrial synergy. Moreover, coal accounts for a relatively high proportion of Beijing's energy structure. Coal is a high-carbon type of energy, and this energy structure is relatively unfavorable for an improvement in the GTFP. The GTFP for Fujian Province was high. A possible reason for this is that the province is rich in natural resources such as forests and hydropower, and the rational use of these resources helps to improve the GTFP. In addition, Fujian Province has formulated a series of policies and measures in energy conservation and emission reduction, which are conducive to promoting production efficiency and environmental protection. Based on the data provided, we can analyze the GTFP of each region as follows:

(1) The GTFP of Beijing reached its peak in 2016 and then showed a downward trend, reaching 0.39 in 2020. The GTFP in Tianjin steadily increased from 2016 to 2018 and then showed a downward trend, reaching 0.56 in 2020. A possible reason for this is that, with the development of the economy, the emphasis on environmental protection and green development in these two regions and cities decreased, leading to a decrease in green production efficiency. The GTFP in Shanghai showed a slight decrease from 2016 to 2017 and then gradually increased, reaching 0.56 in 2020. Shanghai has always been one of the most economically developed regions in China, and it also places great emphasis on green development, which may be one of the reasons for its increasing GTFP year by year. (2) The GTFP in Fujian Province showed a slight decrease from 2016 to 2017 and then increased year by year, reaching 0.88 in 2020. Fujian Province has abundant natural and human resources, and it also pays attention to environmental protection and green development, which may be one of the reasons for its increasing GTFP year by year. The GTFP in Hubei Province showed a slight decrease from 2016 to 2017, followed by an upward trend, reaching 0.65 in 2020. A possible reason for this is that Hubei Province was one of the regions that experienced rapid economic development before the pandemic, while also emphasizing environmental protection and green development. (3) The GTFP in Guangdong Province decreased from 2016 to 2018 and then increased year by year. The GTFP value in 2020 was 0.57. The economic development of Guangdong Province has always been relatively fast, and this province has also faced issues such as environmental protection and green transformation. However, in recent years, the government has strengthened its investment in and management of environmental protection and green development, which may be one of the reasons for its increasing GTFP year by year. The GTFP in Chongqing showed a relatively stable upward trend, increasing year by year from 0.45 in 2016 to 0.50 in 2020. However, the growth rate was relatively slow compared to those of the other pilot areas, at less than 0.5, and it showed a trend of first slowing down and then becoming fast. This was especially true in 2019 and 2020, when the growth rate accelerated; however, these changes were not significant. From a long-term perspective, the GTFP in Chongqing showed a relatively stable state, lacking significant fluctuations. There were obvious differences in the GTFP characteristics between different regions. The GTFP in Fujian Province was significantly higher than that in other regions, while the GTFP in Beijing was relatively low. The GTFP values in each region showed certain spatial distribution characteristics. Geographically, the pilot area can be divided into three regions: the northern, eastern, and central and western regions. Among them, Beijing, Tianjin, and Shanghai belong to the eastern region, Fujian and Guangdong belong to the southern region, and Hubei and Chongqing belong to the central and western regions. The GTFP in the eastern region was generally higher, while that in the central and western regions was generally lower. By analyzing the above data from a regional perspective, it was observed that the eastern region is economically developed. The shadow prices of carbon trading in the eastern region were generally higher and less volatile. This also means that companies in the eastern region pay more attention to emission reduction and explore low-carbon economic models earlier. In addition, the GTFP in the eastern region was generally higher, which may have been related to this region's economic development level and industrial structure. The central region includes the Henan, Hunan, Hubei, and Jiangxi provinces. The shadow price of carbon trading in these regions was lower than that in the eastern region, which reflects the relatively low level of economic development in these provinces and the relatively weak awareness and ability of companies to reduce emissions. However, the GTFP in the central region was still high, indicating that these provinces have a high potential for

economic development. The western region includes provinces such as Xinjiang, Sichuan, Yunnan, and Ningxia, and the shadow price of carbon trading in these regions was also lower than that in the eastern region. However, the GTFP in these regions was generally higher, indicating that these regions have begun to explore low-carbon economic models in terms of economic growth and that they have a high economic growth efficiency.

Table 3. GTFP for all regions of the country in 2016–2020.

Region\Year	2016	2017	2018	2019	2020
Beijing	0.44	0.36	0.39	0.40	0.39
Tianjin	0.62	0.60	0.62	0.55	0.56
Hebei	0.57	0.59	0.57	0.52	0.48
Shanxi	0.55	0.57	0.61	0.57	0.56
Inner Mongolia	0.65	0.74	0.90	1.01	0.85
Liaoning	0.52	0.52	0.51	0.52	0.51
Jilin	0.34	0.35	0.39	0.41	0.43
Heilongjiang	0.38	0.38	0.41	0.42	0.41
Shanghai	0.55	0.59	0.57	0.57	0.60
Jiangsu	1.03	0.91	0.87	0.81	0.76
Zhejiang	0.75	0.72	0.71	0.72	0.65
Anhui	0.70	0.69	0.73	0.76	0.65
Fujian	1.29	0.80	0.89	0.98	0.88
Jiangxi	0.52	0.53	0.54	0.55	0.52
Shandong	0.81	0.63	0.70	0.61	0.62
Henan	0.47	0.46	0.48	0.44	0.41
Hubei	0.58	0.60	0.65	0.65	0.65
Hunan	0.42	0.42	0.44	0.46	0.45
Guangdong	0.55	0.61	0.59	0.62	0.57
Guangxi	0.45	0.48	0.58	0.69	0.61
Hainan	0.55	0.58	0.54	0.58	0.54
Chongqing	0.45	0.45	0.49	0.49	0.50
Sichuan	0.69	0.72	0.71	0.82	1.02
Guizhou	0.55	0.61	0.62	0.62	0.60
Yunnan	0.86	1.01	1.03	1.00	1.01
Shanxi	0.52	0.53	0.57	0.55	0.54
Gansu	0.38	0.41	0.48	0.50	0.53
Qinghai	0.57	0.59	0.80	1.04	1.04
Ningxia	0.69	0.88	1.01	1.02	0.78
Xinjiang	0.70	0.74	0.85	1.02	0.79

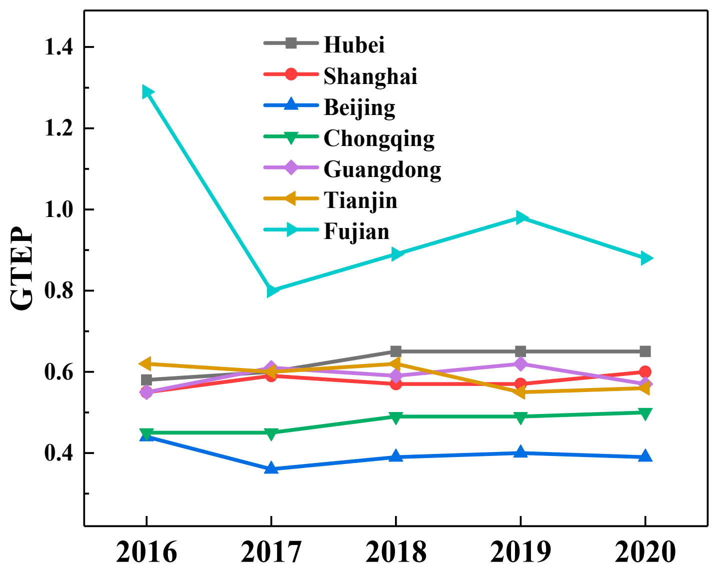

Figure 5. Trends of GTFP in carbon trading pilot areas from 2016 to 2020.

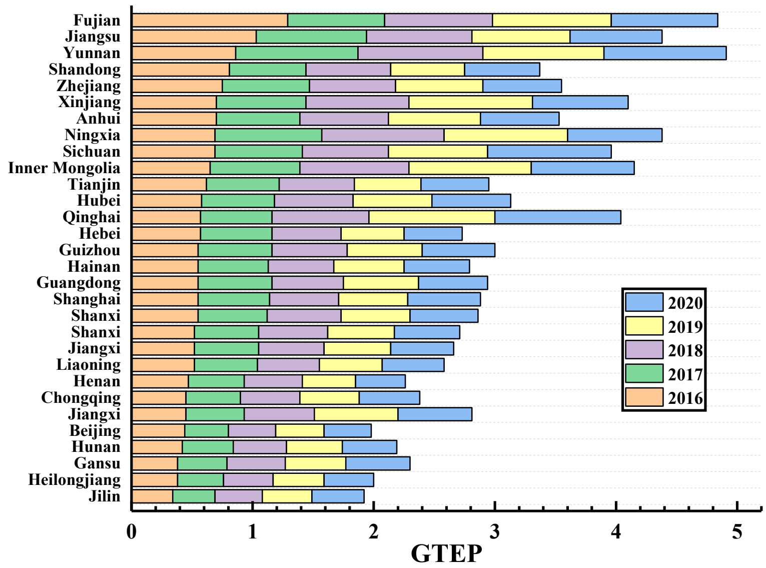

Figure 6. Trends of GTFP in all areas from 2016 to 2020.

5.3. Descriptive Statistical Results of Variables

It can be seen from Table 4 that the sample mean of the GTFP is 0.627, the standard deviation is 0.18, the minimum value is 0.352, and the maximum value is 1.036, indicating that the GTFP varies greatly among different provinces and years. The sample mean of the shadow price (cp) of carbon is 7.366, the standard deviation is 0.665, the minimum value is 5.97, and the maximum value is 9.148, indicating that there are great differences in the shadow price of carbon trading between different provinces and years.

Table 4. Descriptive statistical results of variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
GTFP	150	0.627	0.18	0.352	1.036
cp	150	7.366	0.665	5.97	9.148
pgdp	150	10.98	0.392	10.279	11.994
expand	150	8.595	0.549	7.225	9.758
indstr	150	52.591	7.841	42.4	83.7

5.4. Benchmark Regression

Table 5 shows benchmark regression results. The coefficient of the cp in column (1) to column (4) was at the level of 10%, which is significantly negative, indicating that the shadow price inhibited the GTFP of the power industry. These results show that, when we only consider the impact of the carbon shadow price on the GTFP, the coefficient is negative and significant, and when the carbon trading price increases, the GTFP will decrease. When we simultaneously controlled for the per capita GDP, the local fiscal general budget expenditure, and the tertiary industry added value as a proportion of the GDP, the coefficient of the carbon shadow price was still negative and significant, indicating that this negative correlation does not come from the influence of other variables. In addition, we also used a fixed-effect model, and the results showed that this negative correlation was common among individuals. Therefore, Hypothesis 1 was validated.

Table 5. Benchmark regression.

	(1)	(2)	(3)	(4)
	GTFP	GTFP	GTFP	GTFP
cp	−0.0406 **	−0.0421 **	−0.0418 **	−0.0248 *
	(0.02)	(0.02)	(0.02)	(0.01)
pgdp		0.0493	0.0700	0.2466 **
		(0.09)	(0.10)	(0.10)
expand			−0.0386	−0.0763
			(0.06)	(0.05)
indstr				−0.0125 ***
				(0.00)
_cons	0.9264 ***	0.3961	0.4979	−0.5837
	(0.15)	(1.01)	(1.03)	(0.76)
N	150	150	150	150
r^2_within	0.0188	0.0296	0.0413	0.2090

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.5. Heterogeneity Test

In order to further verify the other hypotheses proposed in this paper, four groups of experiments were carried out, as shown in Table 6. The differences between the carbon emission technology innovation group and the non-technology innovation group were divided according to the level of carbon emission reductions per unit of power generation in each region. The carbon emission reductions of the technology innovation group were higher than the average, and the carbon emission reductions of the non-technology innovation group were lower than the average. The experimental results are shown in Table 6. Column (1) shows the non-carbon emission trading pilot area. Column (2) shows the carbon emission trading pilot area. Column (3) shows the carbon emission reduction technology innovation group. Column (4) shows the non-carbon emission reduction technology innovation group.

Table 6. Heterogeneity test results.

	Non-Pilot Areas	Pilot Areas	Non-Technological Innovation Groups	Technological Innovation Groups
	GTFP	GTFP	GTFP	GTFP
cp	0.0373	−0.0353 *	0.0157	−0.0882 *
	(0.02)	(0.02)	(0.0228)	(0.0443)
pgdp	0.7207 ***	0.3101 ***	0.2661 **	0.2377 **
	(0.11)	(0.11)	(0.1114)	(0.0966)
expand	−0.0159	−0.0724	−0.1011 **	−0.0673
	(0.04)	(0.08)	(0.0447)	(0.0622)
indstr	−0.0230 ***	0.0014	−0.0148 ***	−0.0126 ***
	(0.00)	(0.01)	(0.0038)	(0.0036)
_cons	−6.4235 ***	−1.9187 **	−0.7642	−0.0955
	(1.46)	(0.91)	(0.8637)	(0.8911)
N	35	115	70	80
r^2	0.8814	0.2119	0.2634	0.2700

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The coefficient of cp in the non-pilot areas was 0.0373, which was not significant, indicating that the shadow price of carbon in the non-pilot area had no significant impact on the GTFP. In the pilot areas, the coefficient of cp was −0.0353, which was significantly negative, indicating that the higher the value of the cp, the lower the GTFP. The significance of this relationship was 10% (represented by an asterisk). This successfully verifies Hypothesis 2: the carbon trading pilot intensified the inhibitory effect of the shadow price of carbon on the GTFP.

For the non-technological innovation group, the coefficient of cp (0.0157) fails to reach statistical significance, suggesting an absence of a substantial relationship between the carbon shadow price and the GTFP within this group not engaged in carbon emission reduction innovations. In the technological innovation groups, the coefficient of cp was −0.0882, which was significant at the 10% level, indicating that the inhibitory effect could be alleviated. This successfully verifies Hypothesis 3: carbon emission reduction technology innovations alleviated the inhibitory effect of the shadow price of carbon on the GTFP.

6. Discussion

Our research provides a real price perspective for the carbon emission trading market. We have three findings: (1) shadow prices can suppress GTFP; (2) in the carbon trading environment, this inhibitory effect is more pronounced; and (3) under technological innovation, this inhibitory effect can be alleviated. Our research can also be supported by Wu et al.'s, and Peng and Liu's research [46,47]. Their research also emphasizes that excessive shadow prices are a burden on emission reduction. Our research precisely validated this viewpoint through three regression analyses.

The shadow price of carbon is usually the cost to electric power companies of reducing carbon emissions. If the shadow price of carbon trading is higher, the cost to companies will be higher, which inhibits the investment of companies into environmental protection. This leads to poor environmental performance for companies, which, in turn, affects the GTFP. The shadow price of carbon has an impact on corporate governance. If companies become burdened with higher carbon transaction costs, it may cause pressure on their financial situation, which may affect the stability and transparency of their governance structure. This may lead companies to reduce their technological investment in carbon emission reduction, which, in turn, affects the GTFP score.

Therefore, power companies need to seek a balance between carbon emission control and emission reduction investment. It is necessary to formulate scientific carbon emission control strategies and technological innovation investment plans to ensure that companies can maintain reasonable cost expenditures while reducing carbon emissions. Companies can achieve this balance by formulating investment objectives and assessment mechanisms for technological development and by establishing a carbon emission data tracking and control system. In order to strengthen the management of the GTFP, the industry needs to establish management institutions and processes, strengthen data collection and analysis, formulate goals and plans, and supervise and evaluate the implementation of carbon emission reduction by various companies. In addition, companies also need to strengthen their disclosure of relevant information and improve the transparency and credibility of the relevant data sources.

The inhibitory effect of the shadow price on the GTFP may bring certain risks. Therefore, the power industry needs to strengthen its risk management and formulate corresponding strategies and emergency plans. In addition, power companies need to strengthen communication and cooperation with policy-making institutions and carbon trading markets to better respond to changes in carbon trading policies and markets. Companies can reduce the cost of carbon emissions by improving their innovation capabilities, thereby reducing the inhibitory effect of carbon trading shadow prices on the GTFP. Companies need to strengthen their technology research and development and innovation investments and improve the quantity and quality of patents in order to achieve a win–win situation of technological innovation and carbon emission control. In addition, companies and research institutions can promote the common development of technological innovation and carbon emission control through cooperation and promote the development of the entire power industry.

7. Conclusions and Recommendations

This study explored the impact of carbon emission shadow prices on the GTFP of the power industry and drew conclusions through empirical research. The results show that the shadow price of carbon emission trading has a significant impact on the GTFP of the power industry. Specifically, when the shadow price of carbon emission trading is small, the GTFP of the power industry performs better, and its carbon emission level is relatively low; when the shadow price of carbon emission trading is high, the GTFP of the power industry is relatively poor, and its carbon emission level is relatively high. Therefore, we provide the following four suggestions.

(1) Government departments should promote the development of a carbon trading market, promote the transparency and stability of market prices, improve the enthusiasm of electric power companies to participate in market transactions, strengthen the supervision of the carbon trading market, formulate reasonable carbon emission trading prices, and avoid price distortions.
(2) In order to reduce the cost of carbon trading, companies can adopt more environmentally friendly technologies. In addition, companies can reduce the cost of carbon trading by participating in the competition of the carbon trading market and by finding lower-cost carbon quotas. Companies should carefully evaluate their carbon transaction costs and formulate corresponding strategies to control their costs so as to ensure their sustainable development. Companies can also increase their use of renewable energy, which can not only reduce carbon emissions, but also reduce costs.
(3) Companies can improve their energy efficiency to reduce their energy consumption and carbon emissions, including by adopting more efficient equipment and technologies, optimizing energy management, and other measures. By improving their energy efficiency, companies can use more environmentally friendly technologies to reduce their carbon emissions.
(4) In order to reduce the impact of competition among power companies, it is recommended that power companies consider adopting a variety of carbon trading methods, such as carbon emission trading, carbon neutralization trading, and carbon emission reduction certification, to reduce carbon trading costs. Moreover, the flexibility and competitiveness of companies can be improved through diversified carbon trading methods. At the same time, it is suggested that electric power companies can strengthen cooperation and innovation, jointly promote the development and application of emission reduction technologies through joint development and cooperative research, reduce carbon transaction costs, and improve their competitiveness.

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