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Have China's Regional Carbon Emissions Trading Schemes Promoted Industrial Resource Allocation Efficiency? The Evidence from Heavily Polluted Industries at the Provincial Level

Chunhua Lu and Hong Li *

School of Economics, Peking University, Beijing 100871, China
* Correspondence: lihong2008@pku.edu.cn

Abstract: Based on the data of A-share listed companies in China, this paper examines how China's regional carbon emissions trading scheme (ETS) affects the resource allocation efficiency of China's provincial heavily polluted industries through the DID method. The empirical results show that China's regional carbon ETSs have reduced the TFP dispersion of enterprises in the industry, thus improving the industries' resource allocation efficiency. The heterogeneity analysis shows that China's regional carbon ETSs have more significantly promoted the resource allocation efficiency in industries with high competition and high external financing dependence, while the policy effects in industries with low competition and low external financing dependence are less significant. Further mechanism analysis shows that, on the one hand, China's regional carbon ETSs have promoted the flow of capital resources from low-TFP enterprises to high-TFP enterprises. On the other hand, China's regional carbon ETSs have promoted low-TFP enterprises to improve TFP to a higher degree than high-TFP enterprises, which reduces the TFP dispersion among different enterprises in the industry. In addition, China's regional carbon ETSs have promoted the market share of high-TFP enterprises and restricted low-TFP enterprises entering the market, which raises the TFP threshold for new enterprises entering the market.

Keywords: emissions trading scheme; enterprise production efficiency; productivity dispersion; resource allocation; heavily polluted industries

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1. Introduction

As the largest developing country, China has experienced rapid economic growth in the past 40 years, but it has also brought about serious energy consumption and emission problems. Since 2016, China has surpassed the United States as the world's largest carbon emitter. In 2021, China's carbon emission accounted for 33% of the global total, which is 2.2 times that of the United States. Faced with the pressure of emission reduction, China actively uses a variety of policy tools to reduce greenhouse gas emissions. As an important environmental regulation means to reduce greenhouse gas emissions through market mechanisms, the emissions trading scheme (ETS) has been widely used in China. Since 2013, China has successively launched seven regional carbon ETSs. In July 2021, China's national ETS started online trading, and the first performance cycle was successfully completed in January 2022. At present, the carbon ETS is playing an increasingly important role in allowing China to achieve the goal of low-carbon development; in addition, the literature has frequently analyzed the emission reduction and green development effects of carbon ETS in China [1–4] and in other regions, such as EU ETS [5–8] and US RGGI [9,10]. In general, the literature found that carbon ETSs in China, Europe and the United States can promote emission reduction and help realize green development effects, such as the growth of green innovation in enterprises. However, none of the literature has discussed the impact of carbon ETSs on the efficiency of resource allocation whether in China or other countries, which is also an important new topic with significant research value.

Since China's reform and opening up, with the improvement of China's economic system, the optimization of ownership structure and the upgrading of industrial structure, China's economy has achieved a significant increase [11–13]. However, for a long time, China's high economic growth has been accompanied by the extensive development mode, characterized by the inefficient use of resources and high pollution, which has affected the quality of economic development [14,15]. Since the 19th National Congress of the Communist Party of China propounded that China's economy has entered a stage of high-quality development, promoting high-quality economic development is regarded as the most important transformation goal of China's economy [16,17]; many policies should serve to achieve this goal, and environmental policies are no exception [18,19]. As a market-based environmental regulation means, China's carbon ETSs should also serve the high-quality development of the economy while promoting emission reduction [20,21]. Among several indicators of economic operation, total factor productivity (TFP) is generally regarded as the indicator that best reflects the quality of economic development [22–24]. At present, many documents have discussed the impact of China's carbon ETSs on TFP from different levels, such as regions, industries and enterprises, and generally found that China's carbon ETSs have a positive role in promoting TFP [25–27]. Unfortunately, there is no existing literature to discuss the impact of China's carbon ETSs on resource allocation efficiency, which has a significant impact on TFP.

It is generally regarded that the macro TFP is mainly affected by two aspects: one aspect is the micro level of input-output efficiency, that is, the enterprise's TFP; for another aspect, it is the resource allocation efficiency, that is, the allocation of production factors among heterogeneous enterprises [28–30]. Hsieh et al. [28] published a paper on how the resource allocation efficiency affects TFP, which is also the most influential study in the literature on the efficiency of resource allocation so far. Hsieh et al. [28] found that if the resource allocation efficiency of China reached the level of the United States, China's TFP could be increased by 30–50%. Yang [31] found that in 1998–2007, about 56% of the TFP of China's manufacturing industry came from the improvement of enterprises' TFP, and the improvement of resource allocation efficiency also contributed about 31%. In view of the important role that the improvement of resource allocation efficiency plays in the improvement of TFP, more and more documents begin to pay attention to the impact of various policies on resource allocation efficiency. Among them, the research on the impact of environmental policies started relatively late, since relevant research did not appear until 2015. As the pioneering document to study the impact of environmental policies on the resource allocation efficiency, Tombe et al. [32] constructed a heterogeneous enterprise model. They found that the implementation of the environmental standards set, based on pollution intensity, had an obvious asymmetric effect among enterprises with heterogeneous productivity, since low-TFP enterprises need to bear more environmental costs than high-TFP enterprises; indeed, low-TFP enterprises are often forced to withdraw from the market because it is difficult for them to meet pollution discharge standards. Forslid et al. [33] found that, under a certain intensity of environmental regulation, only enterprises with a high TFP will invest more money in green technology, and show higher profitability and cleaner production capacity. If environmental regulation can force low-TFP enterprises to exit and promote the flow of production factors to high-TFP enterprises, it can promote total TFP growth by optimizing resource allocation. The above articles have analyzed the impact of environmental policies on the efficiency of resource allocation from the theoretical level; at the empirical level, the existing empirical articles mainly focus on the impact of China's environmental policies, while there are quite a few empirical articles that take other countries and regions as the research objects. Unfortunately, although some literature have focused on the impact of China's environmental policies on resource allocation efficiency, these studies mainly focus on environmental policies other than carbon ETSs, such as green financial policies [34,35], environmental administrative restraint policies [36,37] and environmental information disclosure policies [38,39]; meanwhile, the research on carbon ETSs and resource allocation efficiency is still blank.

In view of the vacuum of current research on carbon ETSs and resource allocation efficiency, this paper takes the provincial heavily polluted industries in China as the research object and analyzes the impact of China's regional carbon ETSs on the resource allocation efficiency of these industries, which has important theoretical and practical significance. The reason why this paper chooses China's heavily polluted industries as the research object is that most of the industries covered by China's carbon ETSs at present are heavily polluted industries, such as steel, coal, petrochemical and so on; these heavily polluted industries generally have the problem of low resource utilization efficiency to a certain degree, due to local protection, monopoly and other factors. The main contributions of this paper are as follows: Firstly, this is the first time that the impact of China's carbon ETSs on the efficiency of resource allocation is systematically studied, which is of great pioneering significance because it fills in the research gap in this field; Secondly, this study has an important guiding role in further studying the policy effect of carbon ETSs under the framework of resource allocation efficiency and TFP. If we find that carbon ETSs can promote resource allocation efficiency, then based on this study, the further discussion of the contribution rate of enterprises' TFP and resource allocation efficiency in the process of promoting total TFP growth will be another meaningful research issue; Thirdly, when the existing literature analyzes the mechanism of how other environmental regulation policies affect the resource allocation efficiency, they mainly focuses on the discussion of the exit/entry behavior of enterprises and the change in their market share. In this paper's mechanism research part, we also analyze how China's regional carbon ETSs affect the reallocation of production factors among enterprises, thus revealing the micro mechanism of how China's regional carbon ETSs affect the efficiency of industrial resource allocation; Fourthly, when the existing literature uses the DID method to evaluate the policy effect of China's carbon ETSs, the common problem is to over-select the treatment group, that is, the industries or enterprises covered by the treatment group are more than those actually affected by the policy. To solve this problem, we set the provincial heavily polluted industries that are actually impacted by the regional carbon ETSs as the treatment group, and exclude the industries that are not actually covered in the ETSs; however, they are located in the ETS policy implementation area, which helps us more carefully analyze the effect of China's regional carbon ETSs on the sub-industries actually affected by the policies.

2. Research Hypothesis

According to the HK model proposed by Hsieh et al. [28], in an ideal market with a free flow of factors and no distortion, the final TFP of enterprises will be consistent. However, in reality, the existence of distortions, such as monopoly, information asymmetry and local protection, has led to the heterogeneous distribution of enterprises' TFP. The greater the dispersion of enterprises' TFP distribution, the lower the efficiency of resource allocation. For carbon ETSs, improving the efficiency of industry resource allocation is to reduce the dispersion of enterprise TFP distribution in the industry, which may be achieved through the following mechanisms.

Firstly, China's regional carbon ETSs may promote the efficient flow of production factor resources among enterprises with heterogeneous productivity. According to Hsieh et al. [28], an important way to achieve effective resource allocation is the free flow of production factor. For enterprises included in the ETSs, in order to meet the emission reduction requirements, they need to pay a certain "compliance cost", which is used for equipment upgrading, technological innovation and purchase of emission quotas, etc. Since high-TFP enterprises tend to have a more stable financial situation, they will have more sufficient funds to cope with these costs and take emission reduction actions. For low-TFP enterprises, the increase in operating costs is more likely to impact their original production and make it difficult for them to bear the cost of high-quality production factors. In addition, some financial institutions may also raise the threshold of credit support for low-TFP enterprises and are more inclined to provide credit services for high-TFP enterprises. Under the influence of these factors, it will be more difficult for low-TFP enterprises to obtain production factors in the market, which will accelerate the flow of production factors to high-TFP enterprises. According to HK model proposed [28], this process will eventually promote the decline in enterprises' TFP distribution and improve the resource allocation efficiency in the industry.

Secondly, China's regional carbon ETSs may cause the differentiated "innovation compensation effect" among enterprises with heterogeneous productivity. Porter et al. [40] found that, when facing the pressure of environmental regulation, enterprises will consciously carry out more technological innovation activities to improve resource utilization efficiency and enhance their competitiveness, resulting in the so-called "innovation compensation effect". Gray et al. [41] found that enterprises with heterogeneous productivity have a differentiated "innovation compensation effect". When implementing environmental regulations such as ETS, the government often enacts stricter enforcement on low-TFP enterprises, which makes low-TFP enterprises face higher pressure to reduce emissions. In addition, as mentioned above, low-TFP enterprises have more limited access to production factor resources. Under the government's high pressure supervision and limited access to production factor resources, compared with high-TFP enterprises, low-TFP enterprises may have a stronger motivation to reduce emission reduction costs through technological innovation, making them actively improve their TFP to survive in the market. Eventually, the TFP of low-TFP enterprises still cannot exceed that of high-TFP enterprises, but the rate of their TFP increase may be higher than that of high-TFP enterprises; this ultimately reduces the TFP dispersion among enterprises in the industry, thus improving the resource allocation efficiency in the industry.

Thirdly, China's regional carbon ETSs may affect the market share change and exit/entry behavior of heterogeneous productivity enterprises. In the face of China's regional carbon ETSs, for enterprises with particularly low-TFP, due to their relatively poor technological foundation and lack of innovation funds, it is difficult to make up for the emission reduction costs through the "innovation compensation effect". In addition, these enterprises find it difficult to obtain high-quality production factor resources to produce high-quality products, and their products are increasingly lack competitiveness in the market, which aggravates the reduction in their market share. Finally, the enterprises with extremely low-TFP are either eliminated by the market or merged. In addition, China's regional carbon ETSs may raise the productivity threshold for enterprises to enter the market, because low-TFP enterprises know that they will lack competitiveness even if they enter the market, which reduces their enthusiasm to enter the market newly. Finally, only high-TFP enterprises are more inclined to enter the market newly, which is helpful to improve the resource allocation efficiency in the industry.

To sum up, we propose the following hypothesis:

H1. *China's regional carbon ETSs can reduce the TFP dispersion of enterprises in the industry, thus improving the resource allocation efficiency in the industry.*

3. Research Design and Methodology

3.1. Methodology

3.1.1. The DID Method

The double difference method (DID) is a widely used method for evaluating policy effects, which can quantitatively estimate the effect of a specific policy on the policy implementation object [42]. Due to the different starting time of China's regional carbon ETSs, we construct a multi-period DID model in Equation (1), in order to evaluate the effect of China's regional carbon ETSs on the resource allocation efficiency of China's provincial heavily polluted industries.

$$\mathrm{TFPdis}_{\mathrm{pit}} = \alpha_0 + \beta \mathrm{DID}_{\mathrm{pit}} + \Sigma\delta \mathrm{X}_{\mathrm{pit}} + \mu_{\mathrm{i}} + \gamma_{\mathrm{p}} + \nu_{\mathrm{t}} + \varepsilon_{\mathrm{pit}} \quad (1)$$

At present, the most common way that the existing literature uses the DID method to evaluate the effects of China's regional carbon ETSs from the industry level, is to take the provincial aggregation industry as the treatment group [43,44]. Since China's regional carbon ETSs only cover some industries of the regional carbon regions, the general defect of the above research is the over-selection of treatment groups. For example, many industrial sub-industries in the regional carbon provinces, such as computers and clocks, are not affected by the ETS; if the aggregated industrial industries in the regional carbon provinces are simply taken as the processing group, we cannot examine the impact on the sub-industries that are really covered by the ETS while the regression results include the spillover effect on industries not affected by the ETS. Therefore, it is more reasonable to take the sub-industry actually affected by the ETS policy in the ETS implementation areas as the treatment group [45,46]. In this paper, we also use regional sub-industry data. Specifically, we take the provincial-level heavily polluted industries actually affected by China's regional carbon ETSs in the ETS implementation areas as the treatment group; meanwhile, we take the provincial-level heavily polluted industries that have not been impacted by ETS policy in the ETSs implementation areas, and the provincial-level heavily polluted industries in regions where ETSs are not implemented, as the control group.

In Equation (1), $TFPdis_{pit}$ is the explained variable that reflects the efficiency of industrial resource allocation, where p represents region, i represents industry and t represents year. $DID_{pit} = Policy_{pi}{*}Time_t$ is the treatment dummy, where $Policy_{pi}$ represents whether it is a treatment group. If the industry i is impacted by China's regional carbon ETSs in region p, $Policy_{pi} = 1$, otherwise $Policy_{pi} = 0$; $Time_t$ represents the time of policy implementation, if industry i in region p is impacted by China's regional carbon ETSs after time t, $Time_t = 1$, otherwise $Time_t = 0$ (the policy implementation time of each regional carbon ETS is as follows: For Beijing\Tianjin\Shanghai and Guangdong regional carbon ETSs, $t \geq 2013$; For Chongqin and Hubei regional carbon ETSs, $t \geq 2014$; For Fujian regional carbon ETS, $t \geq 2016$). X_{pit} are control variables, including provincial and industrial control variables. In addition, μ_i, γ_p and ν_t represent the individual fixed effect of a given heavily polluted industry i in province p, the regional fixed effect and the time fixed effect, respectively. ε_{pit} represents the random error term.

3.1.2. The Event Study Method for Parallel Trend Test

The premise of using the DID method is that the treatment group and control group have the same parallel trend before being affected by the policy [47]. For this paper, before being affected by China's regional carbon ETSs, there should be no significant difference in the change trend of resource allocation efficiency between the treatment group industry and the control group industry. Referring to Liu et al. [48], we use the event study method and construct a model, shown in Equation (2), to test whether the parallel trend is satisfied.

$$\begin{aligned}\mathrm{TFPdis_{pit}} = \alpha_0 \quad & + \textstyle\sum_{s=1}^{5} \beta_{pre\_s}\mathrm{DID_{ipre\_s}} + \beta_{current}\mathrm{DID_{icurrent}} \\ & + \textstyle\sum_{s=1}^{5} \beta_{post\_s}\mathrm{DID_{ipost\_s}} + \Sigma\delta \mathrm{X_{Pit}} + \mu_i + \gamma_p + \nu_t + \varepsilon_{pit}\end{aligned} \tag{2}$$

In Equation (2), DID_{ipre_s}, $DID_{icurrent}$, DID_{ipost_s} represent the interaction between the year dummy variable and the policy dummy variable before, during and after the industry is affected by the ETS, respectively. If the parallel trend is satisfied, the coefficient of DID_{ipre_s} should be statistically insignificant, that is, $\beta_{pre\_5} - \beta_{pre\_2}$ should be insignificant; since we set the first year before the industry was hit by the ETS as the basic year, there is no independent variable β_{pre_1}.

3.1.3. The PSM–DID Method for Robustness Test

The double difference method (DID) is applicable to the random natural experiment of the experimental group, that is, it is assumed that the experimental group and the control group are almost the same except for the experimental variables of the policy impact. The implementation of China's carbon trading policy may not be randomly assigned pilot areas, which may lead to sample selection bias. In view of this situation, after the benchmark

DID regression, based on Equation (1), it is necessary to use the propensity score matching method (PSM) to build a PSM–DID model for robustness evaluation.

The basic idea of the PSM method is derived from the matching estimator. On the premise of clearly distinguishing between the processing group and the control group, if industry i belongs to the processing group, it is necessary to find a certain industry j in the control group, so that the observable values of individual i and individual j are as similar as possible (matching). The PSM method can reduce the endogenous problems caused by sample selection bias. In this paper, the specific idea is to use the Logit model, take the policy dummy variable as the explained variable and take the control variable used in Equation (1) as the corresponding matching variable, and then use the nearest neighbor 1:4 matching method for sample matching. Finally, we regress again based on the matching data.

3.2. Explained Variable

The explained variable $TFPdis_{pit}$ reflects the efficiency of industrial resource allocation. Referring to Hsieh et al. [28], the greater the difference in the TFP between enterprises within the sector is, the more serious the misallocation of resources is. Therefore, the mainstream practice in the current literature is to use the dispersion of enterprises' TFP to measure the industrial resource allocation efficiency; representative indicators include the difference between the 90% and 10% quantiles [28,36], the difference between the 75% and 25% quantiles [49,50] and the standard deviation [51] of TFP of all enterprises in the industry. In our research, we first calculate enterprises' TFP based on the LP method [52]; then, for a given heavily polluted industry i in province p in year t, we use the difference between the 90% and 10% quantiles of the TFP in all the enterprises as the explained variable. When β in Equation (1) is significantly negative, it shows that China's regional carbon ETSs have significantly reduced the dispersion of enterprises' TFP, thus improving the efficiency of industrial resource allocation.

3.3. Control Variables

This paper selects a series of influencing factors that can reflect industry characteristics and regional characteristics as control variables based on the existing literature [36,49,53].

The control variables at the industry level include the following: (1) Industry average wage level (lnwage): The wage level directly affects the labor cost of enterprises, and enterprises with heterogeneous TFP will adopt different methods, such as factor substitution, human capital accumulation and technological innovation, in order to deal with the raise of their labor cost [54,55]; this may affect the TFP distribution of the industry. Therefore, this paper takes the industry wage level as a control variable, specifically using the logarithm of average total wages paid by enterprises in the industry to measure it; (2) Industry average asset size (lnavescale): The asset size of enterprises can affect the factor and market dominant power of enterprises in the industry [56], thus possibly affecting the productivity of enterprises and the TFP distribution of the industry. Therefore, this paper takes the asset size of enterprises as a control variable, specifically using the logarithm of the average asset size of enterprises in the industry to measure it; (3) Fixed assets ratio of the industry (fixedasset): The constraint of asset liquidity hinders the effective allocation of financial resources among economic entities, and the improvement of asset liquidity plays an important role in improving the allocation efficiency of financial resources in the industry [57]. As the fixed assets ratio is an important indicator of asset liquidity, this paper takes the fixed assets ratio of the industry as a control variable, specifically using the proportion of the total fixed assets to the total assets of the industry to measure it.

The control variables at the regional level include the following: (1) the economic level (prgdp): Zhou et al. [58] found that the higher the economic development level of the region in China, the higher the efficiency of resource allocation. As per capita GDP is an important indicator of the degree of regional economic development level, this paper takes per capita GDP in the region as a control variable, specifically using the regional per capita GDP calculated based on the base year of 2000 to measure it; (2) Energy utilization level (pec): Yang et al. [53] found that the higher the efficiency of the energy utilization of the region in China, the higher the efficiency of resource allocation. Therefore, this paper takes the energy utilization level as a control variable, specifically using the gross energy consumption per capita calculated by GJ in the region to measure it; (3) Industrial development level (industry): Lu [59] found that the upgrading of the regional industrial development level can significantly reduce regional resource mismatch and improve resource allocation efficiency. Therefore, this paper takes the industrial development level as a control variable, specifically using the proportion of the tertiary industry added value to GDP in the region to measure it; (4) Urbanization level (ur): Zhang et al. [60] found that the improvement of the regional urbanization rate in China has a significant role in promoting the efficiency of regional resource allocation. Therefore, this paper takes the urbanization rate of the region as a control variable, specifically using the proportion of urban population in the total population of the region to measure it.

Specific variables and definitions are shown in Table 1.

Table 1. Variable selection and definition.

Variable Type	Variable Symbol	Variable Definition	Unit
Explained variable	$TFPdis_{pit}$	the difference between 90% and 10% quantiles of TFP of all enterprises for a given heavily polluted industry *i* region *p* at year *t*	None
Treatment dummy variable	DID_{pit}	treatment dummy variable to measure whether industry *i* is impacted by China's regional carbon ETSs in region *p* at year *t*	None
Control variable	$lnwage_{pit}$	the logarithm of the average value of the total wages payable by enterprises in industry *i* at year *t*	None
	$lnavescale_{pit}$	the logarithm of the average asset size of enterprises in industry *i* at year *t*	None
	$fixedasset_{pit}$	the proportion of the total fixed assets to the total assets of industry *i* at year *t*	%
	$prgdp_{pit}$	the real GDP per capita in region *p* at year *t* (the real GDP is calculated based on the year of 2000)	RMB (Ten thousand yuan)
	pec_{pit}	total energy consumption per capita in region *p* at year *t*	GJ
	$industry_{pit}$	the proportion of the tertiary industry added value to GDP in region *p* at year *t*	%
	ur_{pit}	the proportion of urban population in total population in region *p* at year *t*	%

3.4. Data

The data used in our research include enterprise and regional level data. Among them, the enterprise level data we use are the data of Chinese A-share listed companies, specifically from the WIND and CSMAR database. The regional level data are from China Energy Statistics Yearbook, China Environmental Statistics Yearbook, China Science and Technology Statistics Yearbook and regional statistical yearbooks. Referring to Ma et al. [61], we select the industry with codes of B06–B12, C17–C19, C22, C25–C29, C31–C32 and D44 in Industry Classification Standards of China Securities Regulatory Commission (2012) as the heavily polluted industries. The heavily polluted industries impacted by China's regional carbon ETSs are manually sorted and matched by the author, according to the relevant policy documents published annually by each carbon ETS.

In this paper, we processed the original data as follows: (1) ST companies are excluded; (2) Companies whose listing period is less than one year and whose listing is terminated are excluded; (3) Companies with serious data loss are excluded; (4) Companies with less than 5 employees are excluded; and (5) Provincial heavily polluted industries with less than 2 listed companies are excluded.

After the above processing of the data, we finally obtain 1439 sample observations. Descriptive statistics of the variables are given in Table 2.

Table 2. Descriptive statistics of variables.

Variables	Observation Value	Average Value	Standard Deviation	Minimum Value	Maximum Value
Efficiency	1439	1.82	1.03	0	5.02
DID	1439	0.19	0.39	0	1
lnwage	1439	17.91	0.83	16.24	21.98
lnavescale	1439	22.88	1.02	21.50	27.39
ixedasset	1439	29.57	8.94	12.23	53.72
rgdp	1439	4.13	2.06	0.59	10.93
pec	1439	99.91	39.5	33.99	316.44
industry	1439	49.58	11.64	30.71	83.69
ur	1439	61.45	14.67	0.35	89.60

4. Results and Discussions

4.1. The Full Sample Benchmark Regression Results

In this paper, we first conducted a full sample benchmark regression based on Equation (1), and the regression results are reported in Table 3; regression (1) reports the result without adding control variables, regression (2) reports the result with only adding industry control variables, regression (3) reports the result with only adding regional control variables and regression (4) reports the result with both adding industry and regional control variables. From regression (1) to regression (4), we can see that the regression coefficients of the DID items in all the regressions are significantly negative at an at least 5% level, indicating that China's regional carbon ETSs have significantly reduced the dispersion of enterprises' TFP in the provincial-level heavily polluted industries; that is to say, the resource allocation efficiency in these industries has been improved.

Table 3. Benchmark regression results.

Variables	Regression (1)	Regression (2)	Regression (3)	Regression (4)
DID	−0.541 **	−0.553 ***	−0.472 ***	−0.481***
	(0.18)	(0.18)	(0.17)	(0.17)
lnwage		0.212		0.202
		(0.20)		(0.20)
lnavescale		−0.437 **		−0.459 **
		(0.22)		(0.23)
fixedasset		−0.040 ***		−0.039 ***
		(0.01)		(0.01)
prgdp			0.140	0.128
			(0.15)	(0.15)
pec			0.001	0.001
			(0.00)	(0.00)
industry			−0.002	−0.007
			(0.02)	(0.02)
ur			0.023 *	0.024 *
			(0.01)	(0.01)
Constant term	1.921 ***	9.312 **	−0.419	7.887 *
	(0.03)	(4.24)	(1.70)	(4.52)
Observation value	1438	1438	1438	1438
Adjust R^2	0.465	0.480	0.469	0.484
Time fixed effect	Yes	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively. The standard error in this paper is clustered to the individual level.

4.2. Parallel Trend Test

We conduct the parallel trend test based on Equation (2) and the result is shown in Figure 1. As can be seen, $\beta_{pre\_5} - \beta_{pre\_2}$ are not significant, indicating that before the impact of China's regional carbon ETSs, the change trend in the industry resource allocation efficiency of the treatment group and the control group is the same; therefore, the parallel trend is satisfied. We can see that, in the year affected by China's regional carbon ETSs, the coefficient of the dummy variable began to be significantly negative. The possible reason for this is that the local government usually informs the enterprises that will be included in the carbon ETS for a period of time (usually less than one year in advance) before the formal implementation of the ETS. Therefore, the enterprises have a certain time to take response measures in advance, rather than adjust their production and operation behaviors after the implementation of ETS; the policy effect of the ETS also began to appear in this process. Figure 1 also shows that, in the first four years after being affected by China's regional carbon ETSs, the absolute value of the coefficient of the dummy variable increased year by year, and in the fifth year, it began to decline. Such a result indicates that the effect of China's regional carbon ETSs on improving the allocation of industrial resources began in the year of ETS implementation without a time lag; after that, the effect has generally increased year on year in the last four years.

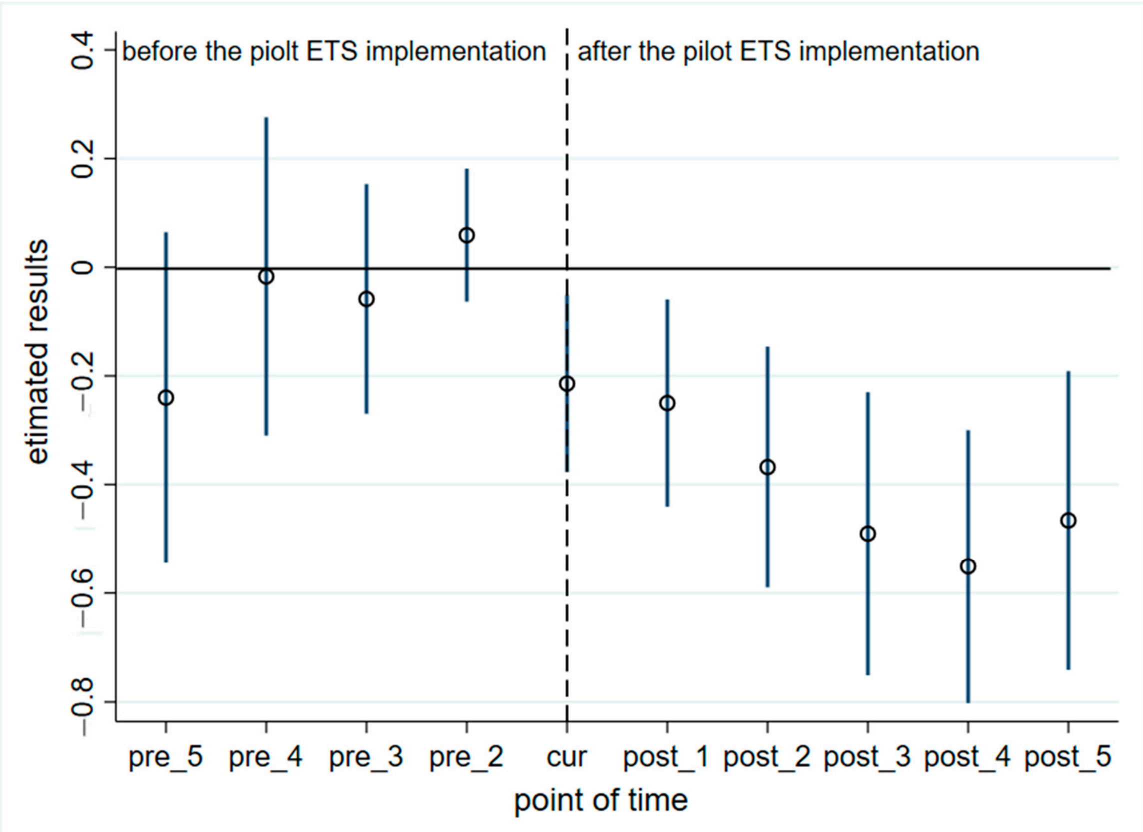

Figure 1. Results of parallel trend test.

4.3. Robustness Test

4.3.1. Placebo Test

In order to further test that the change in resource allocation efficiency in provincial-level heavy pollution industries mainly comes from the implementation of the carbon ETSs, rather than from other unobservable factors, we conduct a placebo test by randomly generating the implementation time of China's regional carbon ETSs, and observe whether the effect on improving the resource allocation efficiency still exists. After 1000 repeats of the random sampling, the *p* value-coefficient scatter diagram of the DID item is obtained, and is shown in Figure 2. We can see that the scatter points of the *p* value of the DID item are concentrated around 0, which is obviously deviated from the actual regression coefficient (in the benchmark regression, the regression coefficient of the DID item is −0.481). In addition, most of the scatter points are located above the dotted line of $p = 0.1$, indicating that most of the coefficients are not significant at a 10% level at least. The above results are inconsistent with the benchmark regression results, indicating that, except for the real ETS implementation year, other virtual policy implementation years cannot significantly promote the decline in the dispersion of enterprises' TFP. The placebo test result shows that the results in the benchmark regression are indeed caused by the carbon ETSs, which proves that the benchmark regression result is robust.

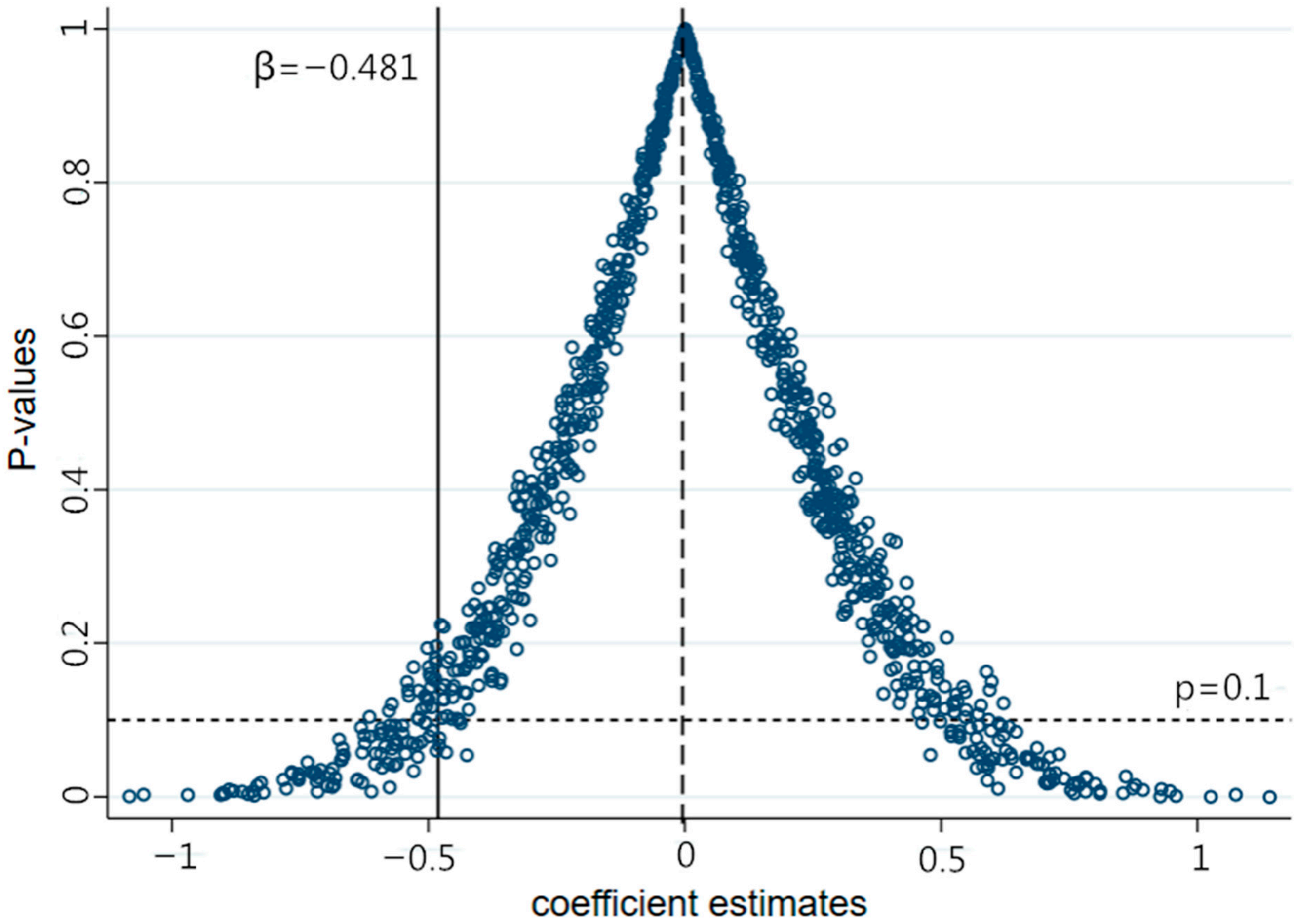

Figure 2. Result of placebo test.

4.3.2. PSM–DID Test

Since there may be an endogeneity problem caused by sample selection bias in our research, we use the PSM–DID model presented in Section 3.1.3 to test the robustness. Before regressing again, we first take the PSM–DID applicability test to determine whether there is a significant difference between the treatment group and the control group after matching, and the result is shown in Table 4; this shows the absolute values of % bias after PSM matching are all less than 10%, which conforms to the evaluation standard of no more than 20%, proposed by Rosenbaum et al. [62].

The regression results after PSM matching are shown in Table 5. We can see that, after PSM matching, the coefficients of DID are significantly negative at a 1% level, regardless of whether the control variable is added. Therefore, the benchmark regression result is robust.

Table 4. Balance test results before and after variable matching.

Variables	Type	Mean		%Bias	*t*-Test	
		Processing Group	Control Group		*t*	$p > \lvert t \rvert$
lnwage	After matching	17.81	17.83	−2.1	−0.25	0.80
lnavescale	After matching	22.82	22.79	3.1	0.34	0.74
fixedasset	After matching	29.41	28.36	9.5	1.04	0.31
prgdp	After matching	4.62	4.48	7.2	0.66	0.51
pec	After matching	96.40	94.63	4.6	0.58	0.56
industry	After matching	46.47	47.46	−8.8	−1.59	0.11
ur	After matching	63.14	62.91	2	0.24	0.81

Table 5. Regression results of PSM–DID test.

Variables	Regression (1)	Regression (2)
DID	−0.417 ***	−0.371 ***
	(0.14)	(0.13)
Control variable	No	Yes
Constant term	1.552 ***	9.761 *
	(0.01)	(4.95)
Observation value	1010	1010
Adjust R^2	0.478	0.495
Time fixed effect	Yes	Yes
Regional fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes

Note: *** and * indicate significance at 1% and 10% levels, respectively.

4.3.3. Heterogeneous Treatment Effect Test

Goodman-Bacon [63] pointed out that the multi-period DID method has a potential heterogeneous treatment effect; in other words, the samples in the treatment group may be used in the control group at other times, but there will be potential bias in the traditional two-way fixed effects model. Goodman-Bacon [63] also proposed the Bacon decomposition method to test the severity of the heterogeneity effect. The core of the test is to split the two-way fixed effects estimator into several 2 × 2-DID combinations, draw the treatment effects and weights corresponding to each 2 × 2-DID combination, then judge whether the heterogeneity problem is serious. In this paper, we first supplement the unbalanced panel data to the balanced panel data with the interpolation method before we conduct the Bacon decomposition. The result is shown in Table 6, from which we can see that, in the net effect of China's regional carbon ETSs on the resource allocation efficiency, 82.9% of the effect comes from the group type of the treatment group and the non-treatment group; this means that most of the effects in this benchmark regression are based on the results of counterfactual tests using the group that has never been treated as a control group, which means that there is no serious heterogeneity of treatment effects in this paper.

Table 6. Regression results of heterogeneous treatment effect test.

2 × 2DID Control Group Type	Average Treatment Effect	Weight
Pre-process group VS post-process group	−0.793	0.076
Post-processing group VS pre-processing group	−0.443	0.095
Process group VS never process group	−0.488	0.829

4.3.4. Other Robustness Test

Firstly, we conduct the robustness test by replacing the explained variable. On the one hand, we continue to calculate the TFP of enterprises based on the LP method, but take the difference between the 75% and 25% quantiles of the TFP of all the enterprises as the explained variable (LP7525); on the other hand, we recalculate the TFP of the enterprises based on the OP method [64], and take the difference between the 90% and 10% quantiles of the TFP of all the enterprises and the difference between the 75% and 25% quantiles of the TFP of all the enterprises as the explained variables, respectively. In Table 7, regression (1) to regression (3) show the regression result when using LP7525, OP9010 and OP7525 as the explained variable, respectively. We can see that all the regression coefficients of DID are still significantly negative at an at least 5% level after replacing the above explained variables, indicating that the benchmark regression result is robust.

Table 7. Regression results of other robustness tests (Prat1).

Variables	Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)
DID	−0.473 **	−0.424 ***	−0.440 **	−0.382 **	−0.565 ***
	(0.16)	(0.15)	(0.15)	(0.19)	(0.19)
Control variable	Yes	Yes	Yes	Yes	Yes
Constant term	8.252 *	6.940 ***	9.069 *	12.720 **	5.899 ***
	(5.87)	(3.98)	(5.20)	(5.54)	(4.03)
Observation value	1438	1438	1438	1071	916
Adjust R^2	0.451	0.484	0.422	0.537	0.513
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

Secondly, we exclude the interference of other policies. In 2017, China put forward the policy of "capacity reduction", and many heavily polluted industries are the key targets of the "capacity reduction" policy. In order to exclude the interference of the "capacity reduction" policy, we retain only the time samples collected before the "capacity reduction" policy was proposed, that is, only the 2007–2017 samples are used for regression, and the result is reported in Regression (4) in Table 7. In addition, China issued the ≪"Twelfth Five-Year Plan" on Air Pollution Prevention and Control in Key Regions≫ in 2012, which defined 19 provincial administrative regions as key air pollution prevention areas; the heavily polluted industries in these key areas may also be affected by this policy. In order to exclude the interference of this policy, we only use the provincial heavily polluted industries in the 19 key areas for regression, and the result is reported in Regression (5) in Table 7. From regression (4) and regression (5) in Table 7, we can see that, after removing the interference of the above two policies, the regression coefficients of DID are still significantly negative at an at least 5% level; therefore, the benchmark regression result in this paper is robust.

Thirdly, in order to avoid the existence of extreme values in variables that may affect the robustness of the regression results, we conduct bilateral tail shrinking and bilateral tail cutting at a 1% quantile of the samples. Regression (1) in Table 8 shows the regression result after bilateral tail shrinking at a 1% quantile, and regression (2) in Table 8 shows the regression result after bilateral tail cutting at a 1% quantile. The regression results show that the regression coefficients of DID are still significantly negative, at least at the 5% level, after bilateral tail shrinking and bilateral tail cutting at the 1% quantile, respectively. Therefore, the benchmark regression result in this paper is robust.

Finally, we add the regions × Time fixed effect to control the impact of economic factors and policy shocks in different regions over time, such as regional industrial policies and regional economic conditions, so as to eliminate the threat of shocks from the regional level to the empirical analysis of this paper. In Table 8, regression (3) shows the regression result after adding the regions × Time fixed effect. It can be seen that the regression coefficient of DID was still significantly negative, at least at the 5% level, after adding the regions × Time fixed effect. Therefore, the benchmark regression result in this paper is robust.

Table 8. Regression results of other robustness tests (Prat2).

Variables	Regression (1)	Regression (2)	Regression (3)
DID	−0.426 ***	−0.331 **	−0.302 **
	(0.16)	(0.15)	(0.13)
Control variable	Yes	Yes	Yes
Constant term	6.461	6.639	5.227
	(4.49)	(5.23)	(4.12)
Observation value	1438	1282	1438
Adjust R^2	0.490	0.494	0.296
Time fixed effect	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes
Regional × Time fixed effect	No	No	Yes

Note: ***, ** indicate significance at 1%, 5% levels, respectively.

5. Heterogeneity Analysis

5.1. Heterogeneity of Industry Competition

Restuccia et al. [65] found that competition has an impact on the efficiency of resource allocation among enterprises. Since different heavily polluted industries in China have different degrees of competition, so the effect of China's regional carbon ETSs on improving industry resource allocation may be different among different industries. In order to examine the heterogeneity of industry competition, referring to Kim et al. [66], we use the HHI-index (Herfindahl Index) to evaluate the degree of industry competition (the larger the HHI-index is, the lower the industry competition is). Specifically, we take the HHI-index of each heavily polluted industry in the year (2012) before the initial launch of China's regional carbon ETSs as the standard; the industries below the median (and including) are selected as high-competitive industries, and the industries above the median are selected as low-competitive industries.

Regression (1) in Table 9 shows the regression result for high-competitive industries, where the explanatory variable DID is significantly negative at a 1% level. Regression (2) in Table 9 shows the regression result for low-competitive industries, where the DID is not significant. The results indicate that the effect of China's regional carbon ETSs on improving the efficiency of industrial resource allocation is more obvious in high-competitive industries. The possible reason is that, in low-competitive industries, monopoly power may hinder the progress and innovation of new technologies, and the exertion of carbon trading and other market mechanisms is limited to a certain extent, which leads to the inefficiency of resource allocation.

Table 9. Heterogeneous Regression Results.

Variables	Regression (1)	Regression (2)	Regression (3)	Regression (4)
DID	−0.422 ***	−0.341	−0.700 ***	−0.272 *
	(0.21)	(0.27)	(0.30)	(0.19)
Control variable	Yes	Yes	Yes	Yes
Constant term	5.889	3.687	6.535	14.543
	(5.77)	(7.86)	(5.58)	(9.45)
Observation value	1017	470	711	727
Adjust R^2	0.439	0.529	0.527	0.436
Time fixed effect	Yes	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes

Note: *** and * indicate significance at 1% and 10% levels, respectively.

5.2. Heterogeneity of Industry Dependence on External Financing

Lou et al. [67] found that environmental regulation can affect the enterprises' external financing constraints, and then further affect the allocation of enterprises' resources [68]. Since different industries have different dependence on external financing in China, so the effect of China's regional carbon ETSs on improving industry resource allocation may be different among different industries. To evaluate the heterogeneity of industries' external financing dependence, referring to Svaleryd et al. [69], we use the ratio of the capital expenditure-operating cash flow to the capital expenditure of an industry, in order to measure the industry's external financing dependence (the higher the ratio is, the higher the external financing dependence is). Specifically, we take the ratio in the year (2012) before the initial launch of China's regional carbon ETSs as the standard; the industries above the median (inclusive) are selected as industries with high-external financing dependence, and industries below the median are selected as industries with low-external financing dependence.

Regression (3) in Table 9 shows the regression result for industries with high-external financing dependence, where DID is significantly negative at a 1% level. Regression (4) in Table 9 shows the regression result for industries with low-external financing dependence, where DID is significantly negative at a 10% level, and the absolute value of the coefficient is smaller than that of high-external financing dependence. The results indicate that the effect of China's regional carbon ETSs on improving the efficiency of industrial resource allocation is more obvious in industries with high-external financing dependence. The possible reason is that, under the carbon trading environment, it is more difficult for low-TFP enterprises to obtain support from financial institutions, which promotes the flow of financial resources to high-TFP enterprises; at the same time, this may encourage low-TFP enterprises to improve their production efficiency to survive in the market competition, and such phenomenon is more obvious in industries with high-external dependence.

6. Mechanism Analysis

In the above, we find that China's regional carbon ETSs have significantly improved the efficiency of resource allocation in the provincial-level heavily polluted industries of the treatment group. Therefore, what is the mechanism to achieve this policy effect? This issue is discussed in the following text.

6.1. The Flow of Production Factors among Enterprises with Heterogeneous Productivity

According to Hsieh et al. [28], when more production factors flow from low-TFP enterprises to high-TFP enterprises, the industrial resource allocation efficiency will be improved. To verify this mechanism, we use the firm-level data of heavily polluted industries from the A-share listing, and construct the model shown in Equation (3); this refers to Nancy [70], in order to verify whether China's regional carbon ETSs promote the flow of labor and capital factors from low-TFP enterprises to high-TFP enterprises.

$$\mathrm{Labor_{it}}/\mathrm{capital_{it}} = \alpha_0 + \beta_1 \mathrm{DID_{it}} + \beta_1 \mathrm{TFP_{it}} + \theta \mathrm{DID} * \mathrm{TFP_{it}} + \mu_\mathrm{i} + \nu_\mathrm{t} + \lambda_p + \varepsilon_\mathrm{it} \quad (3)$$

In Equation (3), $labor_{it}$ and $capital_{it}$, respectively, represent the labor factor and the capital factor input of enterprise *i* at time *t*. To increase robustness, we also use $\Delta labor_{it}$ (the growth rate of $labor_{it}$ compared to last year) and $\Delta capital_{it}$ (the growth rate of $capital_{it}$ compared to last year) as the explained variables. Referring to Peng et al. [71], we use the amount of staffs to measure the labor factor input of an enterprise, and use the net fixed assets to measure the capital factor input of an enterprise. DID_{it} is the double difference item, if enterprise *i* is included in the ETS in year *t*, DID_{it} = 1; otherwise, DID_{it} = 0. TFP_{it} is the TFP of enterprise *i* at time *t*, calculated by the LP method. Plus, μ_i, γ_p and ν_t represent the individual fixed effect, the regional fixed effect and the time fixed effect, respectively. ε_{pit} represents the random error term.

In Table 10, regression (1) and regression (2) report the results with $labor_{it}$ and $\Delta labor_{it}$ as the explained variable, respectively. It shows that *DID*TFP* is not significant, which means that China's regional carbon ETSs have not yet improved the flow of labor resources from low-TFP enterprises to high-TFP enterprises. Regression (3) and regression (4) report the regression results with $capital_{it}$ and $\Delta capital_{it}$ as the explained variables, respectively. We can see that *DID*TFP* is significantly positive, which means that China's regional carbon ETSs have enhanced the flow of capital elements from low-TFP enterprises to high-TFP enterprises.

Table 10. Mechanism analysis—The flow of production factors among enterprises with heterogeneous productivity.

Variables	Regression (1)	Regression (2)	Regression (4)	Regression (3)
	labor	**Δlabor**	**capital**	**Δcapital**
DID*TFP	−0.009	−0.082	0.016 *	0.217 **
	(0.06)	(0.02)	(0.03)	(0.01)
Constant term	0.971 ***	5.162 **	0.356 ***	7.096 ***
	(0.06)	(2.32)	(0.00)	(4.08)
Observation value	7860	7860	7860	7860
Adjust R^2	0.068	0.122	0.094	0.265
Regional fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

6.2. The Difference of "Innovation Compensation" Effect among Enterprises with Heterogeneous Productivity

Gray et al. [41] found that firms with heterogeneous productivity have different sensitivity to the technical compensation effect of environmental regulation. Faced with huge survival pressure and increasingly limited factor resources, low-TFP enterprises are likely to take more active measures to optimize the internal factor allocation of enterprises; eventually the TFP of low-TFP enterprises still cannot exceed that of high productivity enterprises, but the rate of their TFP increase may be higher than that of high-TFP enterprises, which ultimately promotes the decline in the dispersion of enterprises' TFP in the industry.

In order to verify this mechanism, referring to Li et al. [36], we divide enterprises into different quantiles according to their TFP levels, and use quantile regression to evaluate the effect of China's regional carbon ETSs on the TFP of enterprises in each quantile. In Table 11, regression (1) to regression (6) report the regression results at a 15%, 30%, 45%, 60%, 75% and 90% quantile, respectively; the results show that, with the increase in the quantile, the coefficient of DID decreases generally. This result shows that, generally, the higher the existing TFP level of an enterprise is, the smaller the impact of China's regional carbon ETSs on promoting its TTP is, which ultimately leads to a decline in the dispersion of enterprises' TFP.

Table 11. Mechanism analysis—The difference of the "innovation compensation" effect among enterprises with heterogeneous productivity.

Variables	Regression (1)	Regression (2)	Regression (3)	Regression (4)	Regression (5)	Regression (6)
	P15	**P30**	**P45**	**P60**	**P75**	**P90**
DID	0.828 ***	0.845 ***	0.805 ***	0.762 ***	0.674 ***	0.558 ***
	(0.26)	(0.32)	(0.21)	(0.16)	(0.18)	(0.15)
Constant term	−3.142 ***	−3.344 ***	−5.435 ***	−4.702 ***	−2.240 ***	−2.606 ***
	(0.90)	(0.48)	(0.59)	(0.45)	(0.32)	(0.83)
Observation value	7860	7860	7860	7860	7860	7860
Adjust R^2	0.628	0.636	0.634	0.708	0.700	0.614
Regional fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** indicate significance at 1% levels, respectively.

6.3. Market Share Change and Exit/Entry Behavior of Enterprises with Heterogeneous Productivity

According to the view of resource mismatch theory on resource optimization and reallocation, good policy implementation should enable high-TFP enterprises to obtain a higher market share, accelerate the withdrawal of low-TFP enterprises from the market, improve the productivity threshold of new entrants, and ultimately improve the productivity level of incumbent enterprises in the industry [72]. In order to test the above mechanisms, we examine the effect of China's regional carbon ETSs on the market share changes and the exit/into behavior of heterogeneous productivity enterprises, respectively.

Firstly, we investigate how ETSs affect the market share of enterprises with heterogeneous productivity. For all the enterprises in a given heavily polluted industry in a certain province in a certain year, we first selected the top 15% of all the enterprises in terms of TFP. Then, we calculate the ratio of their total added value to the total added value of the regional industry (recorded as share-H). We also select the bottom 15% of all the enterprises in terms of TFP, and recalculate the ratio (recorded as share-L). Then, we replace the explained variables in Equation (1) with share-H and share-L for regression, respectively. In Table 12, regression (1) is the result using share-H as the explained variable, which shows that DID is significantly positive at a 5% level; regression (2) is the result using share-L as the explained variable, which shows that DID is significantly negative at a 10% level. The results show that China's regional carbon ETSs have promoted the market share of high-TFP enterprises, and have inhibited the market share of low-TFP enterprises.

Furthermore, we use the probit regression to investigate how China's regional carbon ETSs affect the exit/entry behavior of enterprises with heterogeneous productivity, referring to Li et al. [36]. Regression (3) in Table 12 reports the impact of China's regional carbon ETSs on enterprises' exit behavior; we can see that *DID*FTP* is not significant, indicating that China's regional carbon ETSs have not yet enhanced the withdrawal of low-TFP enterprises from the market. Regression (4) in Table 12 reports the impact of China's regional carbon ETSs on enterprises' entry behavior; we can see that *DID*FTP* is significantly positive at a 5% level, indicating that the lower the TFP of enterprises is, the lower the probability of entering the market is. The above results show that, although China's regional carbon ETSs have not yet prompted low-TFP enterprises to withdraw from the market, they have already restricted the new entry of low-TFP enterprises into the market, which improves the productivity threshold for new enterprises entering the market.

Table 12. Mechanism analysis—Market share change, exit/entry behavior of enterprises with heterogeneous productivity.

Variables	**Regression (1)**	**Regression (2)**	**Regression (3)**	**Regression (4)**
	Share-H	**Share-L**	**Exit**	**Entry**
DID	0.030 **	−0.011 *	0.028 **	−0.015
	(0.02)	(0.06)	(0.01)	(0.07)
DID*tfp			−0.012	0.008 **
			(0.04)	(0.11)
Control variable	Yes	Yes	Yes	Yes
Constant term	8.204 ***	−0.555 ***	−2.910	−2.741
	(4.02)	(1.86)	(1.87)	(2.26)
Observation value	1438	1438	7628	7740
Adjust R^2	0.348	0.311	0.168	0.241
Individual fixed effects	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Regional fixed effect	Yes	Yes	Yes	Yes

Note: ***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

7. Conclusions and Discussions

In our research, we first calculate the TFP of heavily polluting enterprises using the data of China's A-share listed companies, and further estimate the industrial resource allocation efficiency of China's provincial heavily polluted industries based on the distribution of the TFP of enterprises. Then, we analyze the direct and dynamic effect of China's regional carbon ETSs on the resource allocation efficiency of provincial heavily polluted industries using the DID method. We mainly obtain the following conclusions:

Firstly, this paper finds that China's regional carbon ETSs have reduced the dispersion of the TFP of enterprises in China's provincial heavily polluted industries, thus improving the resource allocation efficiency in these industries; the dynamic effect analysis shows that the effect generally enhances year by year. The heterogeneity analysis shows that China's regional carbon ETSs have significantly promoted the efficiency of resource allocation in high-competitive industries and high-external financing dependence industries, but the effects on low-competitive industries and low-external financing dependence industries are not significant. Therefore, we suggest that, in the process of building China's ETSs, we should strengthen the law enforcement of low competitive industries and low-external financing dependence industries, supplemented by supporting fiscal, tax and financial policies; this is in order to better improve the efficiency of resource allocation in these industries.

Secondly, by performing the mechanism analysis, we found that China's regional carbon ETSs have promoted the flow of capital factor from low-TFP enterprises to high-TFP enterprises. In addition, we found that China's regional carbon ETSs have promoted low-TFP enterprises to improve their TFP by a higher degree than high-TFP enterprises, thus reducing the TFP dispersion among different enterprises in the industry. Meanwhile, China's regional carbon ETSs have enhanced the market share of high-TFP enterprises and have restricted low-TFP enterprises from entering the market, thus raising the productivity threshold for new enterprises entering the market. These conclusions indicate that promoting the flow of factor resources among enterprises with heterogeneous productivity and accelerating the elimination of low-TFP enterprises from the market are important ways to realize the optimal allocation of resources. Therefore, while continuing to strengthen the construction of ETSs, we should actively break down barriers that hinder the flow of factors and accelerate the process of market integration, to better play the role of the market in resource allocation.

This paper is the first study on the impact of China's carbon ETSs on resource allocation efficiency, which is of great pioneering significance. Compared with the conclusion that other environmental policies improve the efficiency of resource allocation by promoting the survival of the fittest in enterprises [34,37], this paper finds that, although the carbon trading policy has raised the productivity threshold for enterprises to enter the market, it has not yet encouraged low-TFP enterprises to exit the market. The possible reason for this is that China's carbon price is still too low, so it is urgent to raise the carbon price to a reasonable level in order to better stage its policy effect of promoting resource allocation.

There is also much room for expansion in this study. On the one hand, at present, the efficiency of resource allocation is often discussed together with TFP in many articles. In addition, the main research direction is to analyze the contribution ratio of enterprises' TFP improvement and resource allocation efficiency improvement to the total TFP improvement; meanwhile, the research conclusions vary greatly in different countries and industries [28,31,73]. Therefore, in the process of China's carbon ETSs promoting the growth of macro TFP at the regional or industrial level, what is the contribution ratio of enterprises' TFP improvement and resource allocation efficiency improvement? Additionally, what is the potential space for further improving macro TFP through improving resource allocation efficiency? These are the issues that this paper will continue to study. On the other hand, the literature begins to pay increasing attention to the impact of environmental and economic policy uncertainty on enterprise emission reduction and productivity [74–78]. For China's carbon ETSs, the operation of each pilot ETS is the responsibility of the local government, rather than the unified responsibility of the state. However, each pilot area faces different emission reduction and economic development objectives in different periods, and each pilot is faced with uncertainty surrounding the environmental and economic policies brought by local governments. How will such uncertainty surrounding environmental and economic policies affect the way in which carbon ETSs are able to improve resource allocation? This is also a problem that we will continue to study.

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