

Article

Can the Carbon Trading Policy Enhance Resource Allocation Efficiency?—An Analysis of the Synergistic Effect of Market Mechanism and Government Intervention

Yunqing Zhao ¹, Debao Dai ¹ , Wei Shao ^{2,*} and Liang Ye ³

¹ School of Management, Shanghai University, Shanghai 200444, China; 13583091550@163.com (Y.Z.); ddb@shu.edu.cn (D.D.)

² Scientific Research Management Department, Shanghai University, Shanghai 200444, China

³ Office of Admissions and Career Services, Shanghai University, Shanghai 200444, China; liangye@shu.edu.cn

* Correspondence: shaow@shu.edu.cn

Abstract: The carbon trading pilot policy is a key policy to achieve low-carbon development through market mechanism. Studying the impact of carbon trading on resource allocation efficiency can provide an important empirical basis to achieve energy saving and green development. This paper delves into the influence of carbon trading on resource allocation efficiency by utilizing the multi-period difference-in-differences based on comprehensive provincial data spanning from 2011 to 2020 in China. The findings show that carbon trading can promote the optimization of capital allocation efficiency but negatively affect the labor allocation efficiency in the pilot areas. This conclusion still holds through various robustness tests. Further research on regional heterogeneity shows that there are significant differences in the impact of resource allocation efficiency and labor allocation efficiency between eastern and western regions. Crucially, the limited scope of the carbon market's direct influence on labor allocation efficiency is highlighted, demonstrating the need for government intervention to amplify its optimization effects based on the synergistic effect. It provides vital empirical insights for China's ongoing pursuit of energy-saving and green development strategies, emphasizing the synergies between market mechanisms and government regulation in fostering sustainable economic transformation.

Keywords: carbon trading; resource allocation efficiency; difference-in-differences with multiple time periods; carbon market; government intervention



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1. Introduction

The first large-scale use of carbon trading can be traced back to the European Union's pioneering Greenhouse Gas Emissions Trading Scheme, which was created in 2005 [1]. Recognizing China's substantial global contributions to emission reduction, the State Council issued a seminal notice in 2011, marking a significant milestone in the establishment of carbon trading market in China [2–4]. This pivotal move designated two provinces and five cities—Beijing, Tianjin, Chongqing, Shanghai, Hubei, Guangdong, and Shenzhen—as the inaugural pilot areas for the policy, aimed at fostering low-carbon development through market mechanisms [5–7]. In 2016, Fujian Province was added to this elite group of policy pilot regions, further expanding the reach and impact of carbon trading efforts [8]. Culminating in the issuance of the “Measures for the Administration of Carbon Emissions Trading (Trial)” in 2021, China's carbon market officially commenced operations, marking a new era in the country's commitment to environmental sustainability and green growth [9,10].

Using market mechanisms, carbon trading, commonly thought as the Carbon Emissions Trading Scheme (ETS), is a significant policy instrument to encourage green development [11–13]. Prior to the creation of the country's market, the ETS—which is the first market-based strategy for reducing greenhouse gas emissions in China—was tested [14].

By August 2023, the national carbon market had facilitated over 243 million tons of carbon emissions transactions, amounting to approximately 11.192 billion yuan, demonstrating its substantial impact and potential for promoting sustainable development.

The data spanning from 2013 to 2020 for the pilot areas are presented in Table 1, which informed the creation of Figure 1. For the purposes of this research, Shenzhen and Guangdong have been combined as a single entity since Shenzhen is a city within Guangdong Province, and the study focuses on provincial administrative regions. Notably, the cumulative trading volumes and monetary amounts vary significantly among the pilot areas. Guangdong and Hubei dominate the market, accounting for over half of the total share, followed closely by the service-oriented cities of Beijing, Shanghai, and Tianjin. In contrast, Fujian and Chongqing have the smallest ETS markets, reflecting their commitment to green development amidst already pristine environments. Interestingly, while Guangdong boasts a large ETS market share and a correspondingly high GDP, Hubei exhibits a substantial ETS market share despite a relatively lower GDP. This observation suggests that both provinces may be categorized as carbon-dependent, highlighting the complexity of economic growth and emission reduction dynamics within different regions.

Table 1. Carbon trading data of pilot areas from 2013 to 2020.

Province or City	GDP (CNY Trillion)	Trading Amount (CNY Million)	Trading Volume (10 k tons)	Pattern
Guangdong	86,170.88875	159,065.6	7755.1	carbon-dependence prov.
Hubei	34,812.87822	168,834.7	7827.6	carbon-dependence prov.
Fujian	31,874.95875	17,138.0	847.0	environmental province
Beijing	27,453.01375	90,577.7	1461.5	service city
Shanghai	29,857.08816	51,842.5	1739.7	service city
Tianjin	16,267.42000	20,103.6	920.1	service city
Chongqing	18,612.52500	5309.5	869.0	environmental city

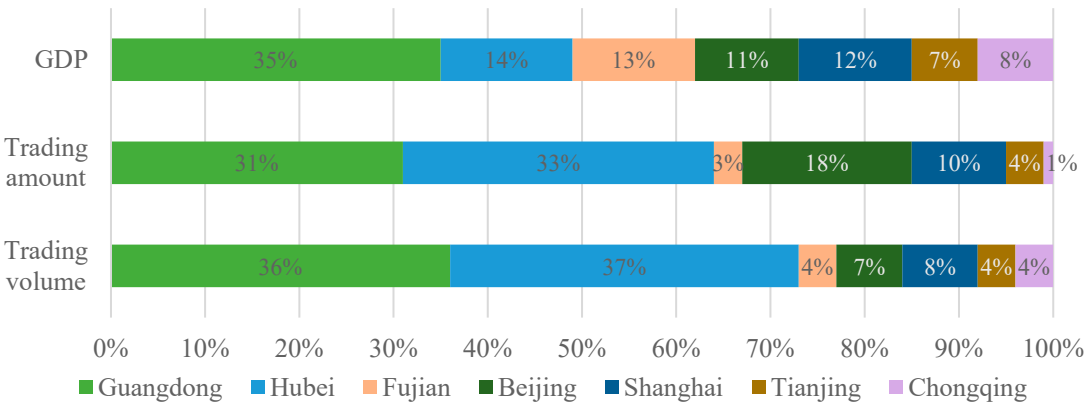


Figure 1. Carbon trading data percent of pilot areas from 2013 to 2020.

Beijing has included 415 enterprises in the carbon trading pilot, demonstrating its determination to promote the development of the carbon market. Guangdong leads the way in carbon trading, with 247 companies actively participating. Although the number of pilot enterprises in Tianjin, Shanghai, and Hubei has not exceeded 200, it does not mean that the influence of these pilots is limited. The ETS pilot was designed to test the effectiveness and feasibility of the policy through practice. Therefore, when selecting pilot enterprises, priority is usually given to those enterprises with industry representative and significant carbon emission and resource consumption characteristics. Although these businesses may represent only a small fraction of the total number of local businesses, their contribution in terms of carbon emissions and resource consumption cannot be ignored. Moreover, through the transmission of market signals and the guidance of industry norms, ETS can also have an indirect impact on companies that are not included in the pilot. This diffusion effect

not only helps to enhance the awareness of energy conservation and emission reduction in the entire industry, but also may further promote the optimization of provincial resource allocation efficiency. Therefore, we should not only evaluate the effectiveness of the ETS pilot based on the number of enterprises, but also consider the direct and indirect effects, as well as the long-term and short-term policy effects.

In the construction and development of the global emissions trading system, the European Union, California (the United States), and Australia set the benchmark for the development of the global carbon market with their unique ETS systems [15].

The EU ETS stands out for its extensive coverage encompassing multiple sectors like power, industry, and aviation, paired with strict regulations including emission caps and quota allocation mechanisms that leverage market forces for emission reductions [16–18]. In contrast, China's ETS, while progressively expanding, currently focuses on the power industry and selected key emitters, not yet achieving comprehensive industry coverage, and, though regulatory enhancements are ongoing, a noticeable gap persists compared to the EU. California's ETS excels through its cap-and-trade program, setting clear emission limits and fostering reductions via market mechanisms, tightly integrated with clean energy and renewable projects, forming a holistic environmental strategy [19,20]. Similarly, China's ETS aligns its emission reduction targets and market mechanisms with its economic and social goals, yet further integration with clean and renewable energy initiatives is required. Australia's ETS, noted for its flexibility and innovation, uses emission benchmarks, allowance allocation, a carbon price guarantee, and flexible carbon credit usage to stabilize market prices and enhance trading efficiency [21]. China's emissions trading system has also made innovations in market design, including paid quota allocation and the participation of financial institutions, but there is still room for improvement in its carbon price stability and trading efficiency.

As a means of market regulation, ETS enables businesses to sell their remaining carbon emission quotas to businesses without quotas at market rates [22]. Encouraging businesses to increase their energy resource efficiency and lower their production-related carbon emissions is the primary objective of ETS [23]. In general, the ETS is an instrument of environmental legislation. The "Pollution Shelter Hypothesis" and the "Porter Hypothesis" are two significant ways that environmental legislation influences the economy in economic theory [24]. According to the "Pollution Shelter Hypothesis", firms may relocate to regions with less environmental oversight as a result of environmental regulations. The "Porter Hypothesis" states that tighter environmental restrictions may lead to more R&D spending, which could enhance productivity. When the theory of company heterogeneity and international trade theory are combined, productivity growth will greatly increase resource allocation efficiency [25].

A thorough examination of the impact of the ETS scale on resource allocation efficiency, and its mechanism for further updating the current ETS, is highly valuable both practically and theoretically, given the backdrop of carbon peak carbon neutrality and the overall green and low-carbon transformation. This paper aims to investigate how China's ETS has affected resource allocation efficiency, as well as the theoretical underpinnings of this policy from the perspective of the complementary roles played by market forces and government action. The efficiency of resource allocation is split into two categories: capital allocation and labor allocation. The market mechanism is measured by the carbon price and the amount of carbon trading, whereas the government interference is analyzed by the percentage of state-owned firms and the penalty. It provides a nuanced understanding of how China's ETS operates and how it can be further optimized to foster more efficient resource allocation in the pursuit of sustainable development goals.

2. Literature Review

2.1. Research Related to Carbon Trading

ETS is a market-driven policy for reducing carbon emissions that aims to lower emission reduction costs, support low-and-green-carbon technical innovation, energy

structure adjustment, and low-and-green-carbon economic and social transformation. Both domestic and international academics are deeply concerned about how carbon pricing will affect emission reduction and how it would affect economic development. Currently, the advantages of ETS from an ecological and economic standpoint are the main focus of relevant field research.

(1) The economic effect of ETS: The impact of ETS on economic growth and green total factor productivity (GTFP) are the two main areas of focus for research on ETS and economic development. Among them, international researchers have employed sophisticated methods such as the PSM-DIDs model [26], the dynamic CGE model [27], and other techniques to examine how the EU Emissions Trading Scheme (EUETS) affects economic growth. They discovered that while the EUETS reduces emissions, it also drives technological advancement, which in turn spurs economic growth. Researchers that have studied China's domestic ETS using the PSM-DIDs method have discovered a link between the ETS and the country's low-carbon economic transformation. This interplay aligns with the Porter Hypothesis, which postulates a win-win scenario of simultaneous economic and environmental benefits [28]. The majority of the literature currently in publication considers GTFP to be the primary indicator of a low-carbon development level, and they reach the conclusion that the ETS can increase the GTFP using various empirical techniques. The majority of academics use the conventional DIDs approach, and it was discovered that the ETS can significantly raise the productivity of the GTFP [29–31]. The enhanced DIDs approach has led some researchers to the same result [32,33]. These findings underscore the potential of ETS as a policy tool to drive sustainable economic growth and environmental improvement;

(2) The ecological effect of ETS: Furthermore, the primary focus of the research on the environmental advantages of ETS is the way in which the ETS reduces emissions [34]. Most academics agree that the ETS can successfully lower emissions. A multi-period DIDs model has been employed to demonstrate the ETS's effectiveness in this regard. However, market mechanisms do not actualize this policy effect. The Chinese government's intervention was crucial in lowering carbon emissions during the carbon market's trial phase [6]. Zhang et al. [35] discovered that the expansion of the secondary industry and foreign direct investment had an impact on carbon emissions as well, which supported the idea that the ETS in the pilot cities had reduced emissions. It has been discovered that policies pertaining to the trading of carbon emissions, economic development, technical innovation, and openness can all greatly lower the level of greenhouse gas pollution and promote a reduction in carbon emissions. On the other hand, the goal for lowering greenhouse gas emissions is hampered by industrial structures and sustainability planning, and forest coverage has little effect on this process [36]. The performance of carbon/energy carbon is found to be greatly improved by the ETS, and its significance in encouraging energy saving and emission reduction is established [37]. The ETS is thought to be a useful policy tool for fostering carbon neutrality. Zhang discovered that while industrial carbon dioxide emissions were greatly decreased, the financial benefit produced by the value of the general industrial output increased with the adoption of the ETS [38]. This underscores the potential for the ETS to achieve both environmental and economic objectives simultaneously.

As a market-based tool to deal with climate change, the ETS has been widely used around the world. From the perspective of stakeholders, governments are looking to the ETS to achieve emission reduction targets, businesses are under pressure to increase costs and invest in emission reduction technologies, and the public has different views on the balance between the environmental benefits of ETS and economic development [39–41]. In terms of policy, ETS not only promotes the achievement of emission reduction targets, but also promotes the development of clean energy and low-carbon technologies, injecting new vitality into economic growth [42,43]. However, with the in-depth implementation of ETS, the government needs to constantly adjust and improve the relevant policies to ensure its fairness and effectiveness. In the broader social context, global climate change has become an important issue to be solved urgently, and ETS, as one of the effective means to deal with

climate change, has been widely concerned by the international community [44]. Governments are rolling out similar emissions trading systems to push global emission reduction targets. At the same time, sustainable development has become an important direction of current social development, and the ETS provides strong support for the realization of sustainable development by promoting the development of emission reduction and clean energy [42].

As an innovative mechanism to deal with climate change, the research on carbon trading has been increasing in recent years. Existing studies affirm the positive role of carbon trading in promoting environmental benefits and economic development, and reveal the potential of the carbon trading market through comprehensive evaluation methods. However, there are also shortcomings in the research, such as insufficient discussions on carbon financial trading rationing mechanism, demand mechanism, price formation and management mechanism, risk supervision and other aspects, and few comparative studies on carbon financial markets in different countries and regions. In the future, the exploration of these blank areas should be strengthened to provide a more comprehensive scientific basis to promote the healthy development of carbon trading markets and promote the green transformation of the global economy.

2.2. Research Related to Resource Allocation Efficiency

Since there is rarely a perfectly competitive market structure, there is resource mismatch, market distortion, and restricted resource flow due to the price of company products not matching their marginal costs. When it comes to researching the effectiveness of resource allocation, Hsieh and Klenow are pioneers [45]. Using microdata from the manufacturing sector, they developed a theoretical model based on heterogeneous companies and monopolistic competitive markets, and they evaluated the macro-efficiency losses brought on by resource mismatch in China, India, and the US. The relationship between the digital economy and resource allocation efficiency has garnered significant attention in recent years. Information asymmetry has decreased, and information mobility has increased with the rapid growth of the digital market, improving the element configuration efficiency and reducing the factor reconfiguration cost [46,47]. It has been determined that the digital economy's network structure has formed and that the networks' collaborative governance impact, which is predicated on the supply chain for labor and the urban network, has begun [48]. Ning, J. et al. aim to integrate the digital economy with the distribution of resources and innovative environmentally friendly technologies [49]. Furthermore, Qian, W. et al. assess the resource mismatch in China and build an efficiency loss model of resource mismatch that includes digital variables of the service field [47]. The proposal suggests a digital dual drive service model and a complete architecture to facilitate resource allocation in shared production [50].

Remarkable achievements have been made in the research of resource allocation efficiency, especially in the fields of market mechanism, government regulation, and technological innovation. Existing studies affirm the decisive role of the market in resource allocation and emphasize the key role of government policies in optimizing resource allocation. However, there are also shortcomings in this research, such as insufficient in-depth discussion of the dynamic, complex, and systematic nature of resource allocation efficiency, and few comparative studies on the resource allocation efficiency of different economies. In addition, there are still gaps in the existing research on the impact of emerging markets and technological change on the efficiency of resource allocation. In the future, we should strengthen the exploration of these fields in order to promote the research on resource allocation efficiency to a deeper and systematic direction.

2.3. The Mechanism and Channel of ETS Influencing Resource Allocation Efficiency

The relationship between the ETS and resource allocation efficiency lies in that it guides the flow of resources to low-carbon and efficient fields through market mechanisms and policy incentives, thus promoting the optimization of the overall economic struc-

ture [11]. In terms of market mechanism, the ETS incentivizes enterprises to reduce carbon emissions by forming a carbon price signal, thereby optimizing the efficiency of resource use [13,44]. The cap-and-trade mechanism allows enterprises to buy and sell emission rights on a cost–benefit basis, which promotes the efficient allocation of resources. In terms of policy incentives, the ETS not only promotes technological innovation of enterprises, reduces carbon emission intensity per unit output, but also promotes the optimization and upgrading of industrial structure, so that more resources flow to low-carbon and efficient industries [41,51]. In terms of regional differences, the economic development level, industrial structure, energy structure and other regional characteristics faced by different provinces in the implementation of the ETS affect the resource allocation efficiency of the ETS at the provincial level [35,52,53]. At the same time, the adaptability of ETS policies in different provinces also has an impact on the improvement of resource allocation efficiency.

The ETS creates a carbon price through market mechanism to encourage enterprises to optimize resource allocation and promote technological innovation and industrial structure optimization through policy incentives to improve resource utilization efficiency; at the same time, considering regional differences, ETS policy design should be optimized to adapt to the actual situation of different provinces and further improve the efficiency of resource allocation. This logical framework not only explains the mechanisms and channels through which the ETS affects the efficiency of resource allocation, but also provides policy recommendations for policymakers to optimize the design of the ETS and improve the efficiency of resource allocation at the provincial level. Future studies can further explore the impact of the ETS on resource allocation efficiency in different industries and different firm characteristics, and how to better play the role of the ETS in promoting resource efficient allocation and sustainable development through policy innovation.

Compared with the existing literature, the interaction mechanism between resource allocation efficiency and the ETS under the framework of China's carbon emission regulations is still a field that needs to be further explored. Previous studies have mostly focused on the micro level of firms, with some analyzing the efficiency of capital allocation in detail [54] and others exploring its impact on the labor market [55,56]. From a macro perspective, this study comprehensively examines the impact of the carbon trading system on capital and labor efficiency. This paper systematically constructs a framework for the direct correlation between resource allocation efficiency and China's emissions trading system, which has rarely been explored in previous studies, thus filling a key gap in the research on the drivers of efficient resource allocation in China. This innovation not only broadens the boundaries of existing research, but also lays a solid theoretical foundation and provides abundant empirical support for subsequent research. At the same time, as an effective supplement to the existing environmental regulation literature, this study reveals the unique contribution of China's emissions trading system in improving the efficiency of resource allocation through an in-depth analysis of its implementation, and opens up a new perspective for understanding the complex interactional relationship between environmental policy and economic performance. In conclusion, this study not only provides a novel perspective and solid evidence for insight into the economic effects of China's carbon emission regulations, but also provides valuable reference and inspiration for formulating more efficient environmental policies.

3. Research Design

3.1. Variable Description

(1) Explained variable

Resource allocation efficiency (RAE), which is separated into two components, labor allocation efficiency (LAE) and capital allocation efficiency (CAE), is the variable that is explained in this study. In order to further explore the actual impact of the ETS on the efficiency of resource allocation in China, this paper draws on the research framework of Chen Yongwei and Hu Weimin [57], and adopts the capital misallocation index (Kmis) and labor misallocation index (Lmis) as quantitative tools, which directly reflect the degree of

resource mismatch at the regional level. Specifically, when the absolute value of the $Kmis$ or $Lmis$ increases, the mismatch of the resources becomes more and more significant. This mismatch is manifested in two forms: one is insufficient resource allocation (i.e., $Kmis$ or $Lmis > 0$), which means that some regions or sectors fail to obtain sufficient resource support in terms of capital or labor, and the second is the overallocation of resources (i.e., $Kmis$ or $Lmis < 0$), which reflects the over-concentration of the resources in some regions or sectors and the relative scarcity in others.

(2) Explanatory variable

The ETS interaction term $DIDs = treat_i \times post_{it}$ serves as the explanatory variable. Among the variables, $treat_i$ is a regional dummy variable, with the values of seven pilot areas of the ETS being 1 and the values of other areas being 0. $post_{it}$ is a time dummy variable, and Beijing, Tianjin, Shanghai, and Guangdong started the ETS in 2013, the $post_{it}$ of these provinces was 1 in 2014 and after, and 0 in 2013 and before; Hubei and Chongqing started the ETS in 2014, so the $post_{it}$ of these two provinces took 1 in 2015 and after, and 0 in 2014 and before; Fujian started the ETS in 2016, and the $post_{it}$ of this province took 1 in 2017 and after, and took 0 in 2016 and before; the $post_{it}$ values of the other provinces are all 0. The experimental group comprises seven pilot provinces, and the other non-pilot areas are control groups.

(3) Control variables

Based on the study on the ETS and resource allocation efficiency, we controlled the factors that may affect the research results, including foreign direct investment (fdi) [58], the industrial structure (ind) [1], the per capita GDP ($pgdp$) [59], human capital (hc) [60], the urbanization level (urb) [61], population density (pd) [1], regional energy saving emission reduction targets (t_1, t_2) [62], the innovation level (il) [63] and the degree of industrial agglomeration (iad) [60].

(4) Other variables

The carbon emission level (ce_{it}) refers to the total amount of greenhouse gases produced by a province over a certain period of time. The market mechanism ($market_{it}$) is the core component of the carbon trading system, which guides enterprises and individuals to reduce carbon emissions through supply and demand, price signals, and the optimal allocation of resources, so as to achieve emission reduction targets. This paper uses the carbon price ($price$) and market transaction size ($amount$) for measuring. Government intervention (gov_{it}) refers to the regulation and management of the carbon trading market by the government through the formulation of policies, regulations, and other means, to ensure the stable and efficient operation of the market. This paper uses the proportion of state-owned enterprises ($staog$) and the intensity of punishment ($penalty$) for measuring.

3.2. Data Source

Based on data availability, this study selects panel data from 2011 to 2020 for 30 Chinese province administrative regions (excluding Tibet, Hong Kong, Macau, and Taiwan). The pilot provinces' carbon emission rights exchanges provide the data for the ETS. Additional data are sourced from the China Statistical Yearbook, the China City Statistical Yearbook, the Environmental Statistical Yearbook, and the CNRDS database, which includes information from several Chinese provinces (autonomous regions and municipalities).

Table 2 displays the definition and methodology for calculating variables, and Table 3 displays the variables' distribution.

Table 2. The definition and calculation of variables.

Variable	Full Name	Definition
<i>CAE</i>	Capital allocation efficiency	The absolute value of the capital mismatch index
<i>LAE</i>	Labor allocation efficiency	The absolute value of the labor mismatch index
<i>DIDs</i>	Carbon trading policy	The interaction between the region variable and the time variable
<i>fdi</i>	Foreign direct investment	Foreign direct investment as a share of GDP
<i>ind</i>	Industrial structure	Advanced level of industrial structure
<i>pgdp</i>	Per capita GDP	Logarithm of GDP per capita
<i>hc</i>	Human capital	Per capita years of schooling
<i>urb</i>	Urbanization level	Ratio of non-agricultural population to total population
<i>pd</i>	Population density	Logarithm of total population per square kilometer
<i>t₁</i>	“12th Five-Year Plan” energy conservation targets	The interaction between the target and the corresponding year
<i>t₂</i>	“13th Five-Year Plan” energy conservation targets	The interaction between the target and the corresponding year
<i>il</i>	Innovation level	Logarithm of the number of domestic invention patent applications accepted
<i>iad</i>	Industrial agglomeration degree	The ratio of the number of employed people to the area of the administrative division
<i>ce</i>	Carbon emission level	The carbon emission amount
<i>price</i>	Carbon price	The annual average of daily closing prices
<i>amount</i>	Market transaction size	The annual average of total transaction volume
<i>staog</i>	Proportion of state-owned enterprises	Income from main business of state-owned enterprises
<i>penalty</i>	Intensity of punishment	The intensity of administrative punishment for non-performance

Table 3. Descriptive statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
<i>CAE</i>	300	0.340	0.392	0.009	2.858
<i>LAE</i>	300	0.003	0.342	0.082	1.092
<i>DIDs</i>	300	0.170	0.376	0.000	1.000
<i>fdi</i>	300	0.019	0.018	0.000	0.121
<i>ind</i>	300	2.374	0.129	2.166	2.836
<i>pgdp</i>	300	2.224	0.431	1.140	3.356
<i>hc</i>	300	9.167	0.989	4.222	12.782
<i>urb</i>	300	0.590	0.122	0.350	0.896
<i>pd</i>	300	474.416	709.120	7.864	3949.562
<i>t₁</i>	300	62.950	66.194	0.000	187.000
<i>t₂</i>	300	97.973	101.227	0.000	272.000
<i>il</i>	300	9.570	1.404	5.318	12.285
<i>iad</i>	300	0.026	0.038	0.000	0.217
<i>price</i>	50	29.449	17.748	4.499	87.062
<i>amount</i>	50	0.465	0.524	−0.004	2.718
<i>staog</i>	300	0.346	0.201	0.000	1.000
<i>penalty</i>	300	0.670	1.664	0.000	6.000

3.3. Model Construction

3.3.1. Baseline Regression Model

The DIDs model can be utilized to examine the relationship among the ETS and the efficiency of resource allocation since this policy can be viewed as a quasi-natural experiment. In the conventional DIDs model, policies are implemented over the same

time period in each region, while China's pilot areas have distinct ETS start dates. To address this challenge and accurately assess the impact of the ETS on resource allocation efficiency in China's context, multi-period DIDs models were adopted. These models enabled us to capture the dynamic effects of the ETS, taking into account the varying initiation points of the ETS across different pilot regions. Specifically, based on the timing of the ETS introduction, the treatment and the control groups were constructed with the former comprising regions where the ETS has been implemented and the latter comprising regions yet to adopt the policy or with no plans to do so. The models were built as follows:

$$CAE_{it} = \alpha_0 + \alpha_1 DID + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \quad (1)$$

$$LAE_{it} = \beta_0 + \beta_1 DID + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \quad (2)$$

However, there are some drawbacks to the DIDs model. Firstly, it is highly sensitive to the parallel trend hypothesis, and if there are systematic differences between the treatment group and the control group before the implementation of the policy, it may interfere with the accurate assessment of the effect of the policy. Secondly, the DIDs model may not be able to fully capture all the complex factors in the process of policy implementation, such as the intensity and speed of policy implementation and the degree of response to policies in different regions, which may affect the evaluation of policy effects. To deal with these limitations, a series of robustness tests were subsequently adopted to ensure the accuracy of the DIDs model. Among them, the PSM-DIDs made the treatment group and the control group have more similar trends before the implementation of the policy through propensity score matching, thus alleviating the limitation of the parallel trend hypothesis to a certain extent.

3.3.2. Regional Heterogeneity Model

Through a detailed analysis of the changes in the resource allocation efficiency of the provincial administrative regions with different carbon emission levels under the implementation of carbon trading policy, the following question arises: under the promotion of carbon trading policy, do provinces with different carbon emission levels show an alienation response in resource allocation efficiency? Therefore, this paper introduces carbon emissions into the above model to build a regional heterogeneity model.

$$RAE_{it} = \varphi_0 + \varphi_1 DID \times ce_{it} + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \quad (3)$$

" $DIDs \times ce_{it}$ " represents the interaction term between environmental regulation and the DIDs.

3.3.3. Synergistic Effect Model

The market mechanism and government intervention were introduced into the base regression model to test whether the two variables play a role in the above effects. The models were as follows:

$$RAE_{it} = \rho_0 + \rho_1 DID + \omega DID \times market_{it} + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \quad (4)$$

$$RAE_{it} = \delta_0 + \delta_1 DID + \nu DID \times gov_{it} + \gamma X_{it} + \theta_i + \mu_t + \varepsilon_{it} \quad (5)$$

Among them, $market_{it}$ is the measure of the market mechanism, which is expressed by the carbon price (*price*) and market transaction amount (*amount*). After adding the interaction between the DIDs and the market mechanism, the coefficient ρ_1 captures the carbon market effect when the market mechanism does not exist at all, and ω captures the carbon market effect caused by the market mechanism. The gov_{it} is a measure of government intervention, which is expressed by the proportion of state-owned enterprises (*staog*) and punishment (*penalty*). After adding the interaction between the DIDs and government intervention, the coefficients δ_1 captures the carbon market effect when the

government intervention does not exist at all, and ν captures the carbon market effect caused by the government intervention. The meanings of other symbols are the same as those of the above model.

As illustrated in Figure 2, the entire procedure can be broken down into three sections. Baseline regression comprises benchmark return and several tests (parallel trend test, series of robustness tests, etc.) that must be passed to use the DID model. The second section, titled “Regional Heterogeneity Analysis,” looks at whether the effects of the ETS on resource allocation efficiency vary depending on the region. The analysis of the synergistic mechanism is in the third section. The role of the market mechanism and government intervention were analyzed.

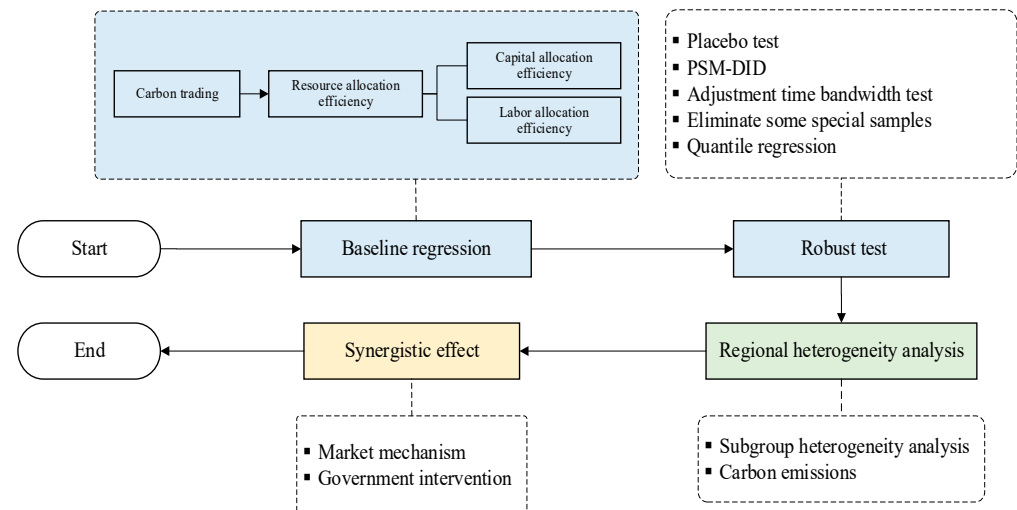


Figure 2. Research framework.

4. Empirical Analysis

4.1. Parallel Trend Test

Strict guidelines must be followed when using the DID model, and before the ETS is put into effect there cannot be any observable distinctions among the control and experimental groups. In order to confirm whether the trend in the sample data prior to the policy pilot was the same, this research employed a parallel trend test. Table 4 and Figure 3 show the findings. The confidence interval of the regression coefficient was not significant before the policy implementation, but it began to be significant after the policy implementation, which indicates that it is reasonable to use the DID model to test this effect, and it has a certain lag and persistence.

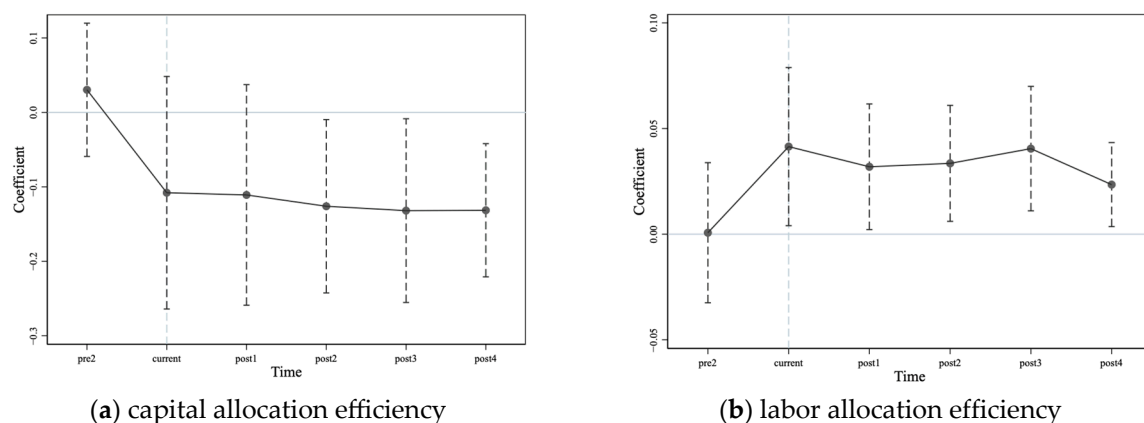


Figure 3. Parallel trend test results.

Table 4. Parallel trend tests of resource allocation efficiency.

Variables	CAE	LAE
pre3	0.0718 (0.0452)	−0.0130 (0.0230)
pre2	0.0096 (0.0367)	0.0007 (0.0195)
current	−0.1067 (0.0877)	0.0411 ** (0.0198)
post1	−0.1150 (0.0811)	0.0328 * (0.0171)
post2	−0.1311 * (0.0693)	0.0362 ** (0.0164)
post3	−0.1194 * (0.0678)	0.0423 *** (0.0150)
post4	−0.1262 ** (0.0538)	0.0256 ** (0.0120)
post5	−0.086 *** (0.0300)	0.0172 ** (0.0170)
Constant	1.4064 (1.2584)	−0.3168 (0.8311)
Observations	300	300
R-squared	0.6588	0.6935

Standard errors are in parentheses; *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

4.2. Baseline Regression Result

The baseline results of Formulas (1) and (2) are listed in Table 5, and the fixed effects of the year, province, and the interaction effect between the province and the year are all controlled.

Table 5. The results of benchmark regression.

Variables	(1) CAE	(2) CAE	(3) LAE	(4) LAE
<i>DIDs</i>	0.0495 (0.1119)	−0.1883 *** (0.0586)	−0.0175 (0.0528)	0.0768 *** (0.0139)
<i>fdi</i>		0.7721 (0.7874)		0.9560 (0.5836)
<i>ind</i>		0.2625 (0.4807)		−0.0363 (0.2464)
<i>pgdp</i>		0.4145 ** (0.1669)		0.3232 *** (0.0898)
<i>hc</i>		−0.0031 (0.0058)		0.0001 (0.0027)
<i>urb</i>		−5.1749 ** (2.1896)		1.0232 * (0.5521)
<i>pd</i>		0.0016 (0.0015)		−0.0015 *** (0.0003)
<i>t₁</i>		0.0018 * (0.0010)		−0.0021 (0.0006)
<i>t₂</i>		0.0008 (0.0005)		−0.0021 (0.0005)
<i>il</i>		−0.0624 * (0.0325)		0.0173 (0.0135)
<i>iad</i>		14.3884 *** (3.8768)		−1.4623 (1.5324)
Constant	0.2542 *** (0.0385)	0.9561 (1.5177)	0.0173 (0.0164)	−0.5250 (0.7898)
Observations	300	300	300	300
R-squared	0.2231	0.6978	0.2320	0.6657

Standard errors are in parentheses; *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

The DID's estimation coefficient of resource allocation efficiency was inconsistent before and after adding the control variables. One explanation could be that there are several variables that affect how efficiently resources are allocated, and because these variables are subject to change, it is simple to generate significant errors when control variables are ignored. Therefore, only the results after adding the control variables were considered. The estimated coefficient of the DIDs was -0.1865 , which is significant at the 1% level according to the results in column (2) when CAE is the dependent variable. This shows that the capital mismatch index can be greatly reduced, and the optimization of the capital allocation efficiency can be encouraged by the establishment of the ETS. The estimating coefficient of the DIDs was 0.0369 , as indicated in column (4) when LAE was the dependent variable, and this was also significant at the 1% level. This suggests that the implementation of the ETS has somewhat increased the labor mismatch index, which is counterproductive to the optimization and improvement of labor allocation efficiency.

The construction of the ETS optimizes the efficiency of capital allocation. The main mechanism is to create financial incentives for enterprises to make capital investments to reduce carbon emissions, such as equipment upgrades and the adoption of clean technologies, thereby effectively directing capital to green projects and optimizing capital allocation. However, the effect of this on the efficiency of labor allocation is not positive. On the one hand, it may lead to the decline of high-carbon emission industries such as the fossil fuel industry, affecting the employment in this field and increasing the difficulty of labor mobility. On the other hand, the cleantech sector is capital-intensive and has low direct demand for labor, further limiting job opportunities in the labor market. In general, while improving the efficiency of capital allocation, the ETS also raises challenges to the labor market in specific industries, which need to be addressed jointly by the government and society to ensure the efficiency and fairness of labor allocation.

4.3. Robustness Analysis

4.3.1. Placebo Test

When years-worth of data are utilized for empirical DIDs analysis, Bertrand noted that sequence correlations may introduce standard error into the analysis, leading to an overabundance of rejections for the null hypothesis in the regression test [64]. As a result, Chetty conducted placebo testing using the nonparametric substitution test [65]. The nonparametric substitution test operates as follows: all the province regions and policy dates are randomly sampled, and eight province regions are chosen as virtual treatment groups, with the remaining provinces serving as virtual control groups. The above steps were repeated 500 times to obtain 500 regression results.

The placebo test findings are displayed in Figure 4. The nonparametric substitution test coefficient distribution's low end is where the DIDs coefficients in Table 5's columns (2) and (4) (-0.1883 and 0.0768 , respectively) are found, indicating that the baseline regression findings above passed the placebo test.

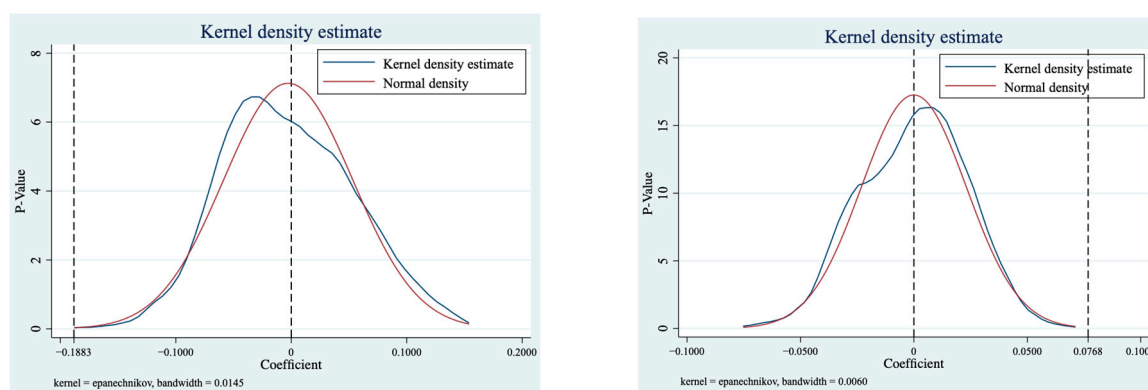


Figure 4. Placebo tests.

4.3.2. PSM-DID

The Propensity Score Matching Difference-in-Differences (PSM-DIDs) model is an advanced research method combining the PSM and the DIDs methods. By matching individuals with similar characteristics in the two groups, the PSM can effectively control the confounding factors that simultaneously affect the implementation of the ETS and the resource allocation efficiency. This helps to more accurately identify the net effect of the ETS on the efficiency of resource allocation. The results of the nearest neighbor matching and kernel matching are shown in Table 6. The regression results were consistent with the above baseline regression results, indicating that the above regression results are basically robust.

Table 6. The results of PSM-DIDs regression.

Variables	The Nearest Neighbor Matching		The Kernel Matching	
	CAE	LAE	CAE	LAE
<i>DIDs</i>	0.233 ** (2.55)	−0.128 *** (−3.18)	0.198 * (2.04)	−0.141 *** (−6.38)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	−2.243 (−0.57)	2.526 *** (4.44)	−3.128 (−0.72)	3.214 *** (4.84)
Observations	67	41	84	56
R-squared	0.727	0.997	0.670	0.993

Standard errors are in parentheses; *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

4.3.3. Adjustment Time Bandwidth Test

Considering the potential impact of specific policy events on research results, adjusting the time bandwidth to more precisely analyze the changes before and after policies is an important step. In 2015, China released its Intended Nationally Determined Contributions (INDCs), a strong set of actions to combat climate change that could have far reaching environmental, economic, and social implications. Therefore, the time window was shortened to 2015 and beyond to specifically examine the effects of the implementation of this policy. The test results are shown in Table 7. The coefficients of the DIDs are significant at 1–5% level, demonstrating the above baseline results pass the robustness test.

Table 7. The regression results after shortening the sample time window.

Variables	(1)	(2)	(3)	(4)
	CAE	CAE	LAE	LAE
<i>DIDs</i>	−0.1492 ** (0.0584)	−0.1850 *** (0.0374)	0.0880 *** (0.0115)	0.0536 *** (0.0125)
Controls	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	0.3519 *** (0.0222)	0.6696 (1.6349)	−0.0050 (0.0056)	−0.4013 (0.6414)
Observations	180	180	180	180
R-squared	0.1651	0.4826	0.2262	0.6002

Standard errors are in parentheses; **, and *** indicate the significance at the 5%, and 1% levels, respectively.

4.3.4. Eliminate Some Special Samples

A series of samples with special properties were excluded for in-depth analysis. We specifically took into account three samples that could impact how accurate the regression results are: first, during the 12th Five-Year Plan period, Beijing and Shanghai, two of China's most economically powerful cities, might have added additional stringent energy conservation and emission reduction policies to the ETS; these extra measures could have affected the baseline regression results; second, Chongqing's distinct features of

economic development—being the only municipality in western China under direct central government authority—may also have an effect on the regression’s findings. Lastly, Fujian introduced the ETS market in 2016, far later than the other provinces and cities.

We conducted three sets of exclusion experiments based on the aforementioned considerations. Firstly, we excluded the data of Beijing and Shanghai in order to eliminate any potential policy overlay effects (results shown in Table 8’s columns (1) and (4)); secondly, we excluded the data of Chongqing in order to eliminate any potential impact from the characteristics of western economic development (results shown in columns (2) and (5)); and thirdly, we excluded the data of Fujian in order to correct for potential bias resulting from variations in the ETS implementation times (results shown in columns (3) and (6)). Following these exclusion studies, it was discovered that the estimated coefficients of the DIDs continued to be significant even after these unique samples were eliminated, which illustrated the stability and dependability of the baseline regression findings of this investigation.

Table 8. The regression results after shortening the sample time window.

Variables	(1) CAE	(2) CAE	(3) CAE	(4) LAE	(5) LAE	(6) LAE
<i>DIDs</i>	−0.1005 ** (0.0373)	−0.01909 ** (0.0706)	−0.1655 ** (0.0673)	0.0287 * (0.0149)	0.0320 ** (0.0151)	0.0271 * (0.0161)
<i>fdi</i>	−0.5203 (0.7399)	0.7926 (0.8449)	0.7767 (0.8275)	1.6752 *** (0.4596)	1.0990 * (0.6201)	1.0754 * (0.6291)
<i>ind</i>	0.2722 (0.3728)	0.2450 (0.4902)	0.2330 (0.4633)	−0.1615 (0.2383)	−0.0550 (0.2526)	−0.0261 (0.2468)
<i>pgdp</i>	0.2388 ** (0.1111)	0.4054 ** (0.1705)	0.4550 *** (0.1561)	0.3244 *** (0.0798)	0.2959 *** (0.0925)	0.2848 *** (0.0972)
<i>hc</i>	0.0017 (0.0026)	0.0038 (0.0054)	0.0027 (0.0052)	0.0020 (0.0034)	0.0001 (0.0027)	0.0008 (0.0028)
<i>urb</i>	−0.2945 (0.9586)	−5.0861 ** (2.2442)	−5.0241 ** (2.1719)	−0.1007 (0.5658)	1.0577 * (0.5997)	1.0640 * (0.5668)
<i>pd</i>	0.0007 (0.0008)	0.0016 (0.0015)	0.0011 (0.0016)	−0.0013 *** (0.0004)	−0.0012 *** (0.0004)	−0.0010 ** (0.0004)
<i>t₁</i>	0.0012 (0.0007)	0.0016 (0.0009)	0.0017 * (0.0009)	−0.0005 (0.0008)	−0.0007 (0.0007)	−0.0007 (0.0008)
<i>t₂</i>	0.0004 (0.0005)	0.0008 (0.0005)	0.0007 (0.0005)	0.0002 (0.0006)	−0.0001 (0.0006)	−0.0001 (0.0006)
<i>il</i>	−0.0285 (0.0190)	−0.0636 ** (0.0291)	−0.0526 * (0.0281)	−0.0113 (0.0124)	−0.0075 (0.0134)	−0.0117 (0.0125)
<i>iad</i>	0.6401 (2.0891)	14.1617 *** (3.8174)	15.2461 *** (4.1291)	−6.7041 (3.9376)	−1.7452 (1.6297)	−2.0512 (1.6091)
Constant	−0.7824 (1.1924)	0.8932 (1.6152)	0.9634 (1.5056)	0.4423 (0.7928)	−0.2659 (0.8461)	−0.3707 (0.8173)
Observations	280	290	290	280	290	290
R-squared	0.3665	0.7004	0.7084	0.651	0.6844	0.6873

Standard errors are in parentheses; *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

4.3.5. Quantile Regression

The regression coefficient will become unstable for many factors, such as outliers, collinearity and heteroscedasticity, which leads to the deviation of the results. Examining how the ETS affects the resource allocation efficiency at various quantile points can help to solve this issue. Table 9 displays the results. The main explanatory variable of labor and capital allocation efficiency, the DIDs, has significant estimation coefficients under the 30%, 60%, and 90% quantiles, demonstrating the stability of baseline regression.

Table 9. Quantile regression results.

Variables	(1) CAE	(2) CAE	(3) CAE	(4) LAE	(5) LAE	(6) LAE
Quantile	0.30	0.60	0.90	0.30	0.60	0.90
<i>DIDs</i>	−0.0878 *** (0.028)	0.2427 *** (0.0577)	1.9248 *** (0.1605)	0.1042 ** (0.0414)	0.1804 *** (0.0596)	0.4190 *** (0.0951)
Control	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Constant	0.1466 *** (0.0330)	0.1868 *** (0.0679)	0.2569 (0.1889)	−0.0418 (0.0488)	0.2302 *** (0.0702)	0.7008 *** (0.1120)
Observations	300	300	300	300	300	300
R-squared	0.0461	0.0779	0.3289	0.3490	0.3497	0.3417

Standard errors are in parentheses; **, and *** indicate the significance at the 5%, and 1% levels, respectively.

4.3.6. Adjusting Control Variable

In order to ensure the reliability and robustness of the research results, a robustness test was conducted by changing the combination of the control variables. In this process, special attention was paid to the variables that could be affected by the ETS, such as the industrial structure and foreign direct investment, as changes in these variables could interfere with the effectiveness of identification. To more accurately assess the robustness of the model, the control variables that could be affected by the ETS were removed, and the coefficients and significance levels of the core explanatory variables were observed to change as a result. The results are shown in Table 10. It can be seen that the regression coefficient was still significant after the removal of control variables, and the above results are robust.

Table 10. The results of adjusting control variable.

Variables	(1) CAE	(2) CAE	(3) LAE	(4) LAE
<i>DIDs</i>	0.0495 (0.1119)	−0.1931 *** (0.0602)	−0.0156 (0.0419)	0.0264 ** (0.0120)
<i>pgdp</i>		0.4076 ** (0.1668)		0.3203 *** (0.0935)
<i>edu</i>		−0.0028 (0.0057)		0.0011 (0.0027)
<i>urb</i>		−4.9928 ** (2.1485)		1.2545 ** (0.4746)
<i>pd</i>		0.0017 (0.0015)		−0.0009 ** (0.0004)
<i>t₁</i>		0.0019 * (0.0011)		−0.0005 (0.0008)
<i>t₂</i>		0.0007 (0.0005)		0.0000 (0.0006)
<i>il</i>		−0.0595 * (0.0318)		0.0144 (0.0160)
<i>iad</i>		14.3713 *** (4.038)		−1.8251 (1.7822)
Constant	0.2542 *** (0.0385)	1.3805 (1.0012)	0.0161 (0.0158)	−0.8816 ** (0.3501)
Observations	300	300	300	300
R-squared	0.2231	0.6930	0.2434	0.6639

Standard errors are in parentheses; *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

4.3.7. Bacon Decomposition

By breaking down the sources of error in the regression model, bacon decomposition identified and quantified the potential factors that may have an impact on the regression

coefficient, ensuring that these conclusions were not based on superficial correlations, but on a more robust statistical foundation. The results are shown in Table 11. It can be seen that the main source of the overall DID estimation results in this paper was the estimation coefficient of the control group that had never been subjected to policy treatment, with a weight as high as 94.1%, while the weight of the control group that had been subjected to policy treatment earlier accounted for 4.2%, which may bring errors, and has little interference with the whole, proving the robustness of the above regression results.

Table 11. The results of bacon decomposition.

Variables	CAE		LAE	
	Weight	Estimate	Weight	Estimate
<i>T vs. Never treated</i>	0.941	0.122	0.941	−0.057
<i>Earlier T vs. Later C</i>	0.016	0.204	0.016	−0.097
<i>Later T vs. Earlier C</i>	0.042	−0.306	0.042	0.142
<i>DIDs estimate</i>		0.105		−0.050

T = treatment; C = comparison.

4.4. Regional Heterogeneity Analysis

4.4.1. Subgroup Heterogeneity Analysis

The effect of the ETS on the resource allocation efficiency may be different due to the regional development, and the social and environmental differences. The samples were divided into three parts: the east, the middle, and the west, and the grouping heterogeneity was analyzed. The results are displayed in Table 12. The regression results are organized by region, with Columns (1) and (4) presenting findings for the eastern region, Columns (2) and (5) showing results for the central region, and Columns (3) and (6) detailing outcomes for the western region. These results show that the effect of the ETS on the efficiency of capital and labor allocation is significantly different in different regions. Specifically, the ETS in the eastern region had no significant effect on the efficiency of both capital and labor allocation, while the ETS in the middle was different. The middle ETS significantly affected the efficiency of capital allocation, but had no significant effect on the efficiency of labor allocation. In contrast, the ETS in the western region had a significant effect on the efficiency of labor allocation. This difference may be due to a combination of factors, including differences in economic structure, different levels of carbon emissions across regions, and differences in the ability of governments to implement policies. The eastern region, with its more developed industrial structure and strong adaptability, may have already achieved its carbon reduction targets to some extent, thus diminishing the direct effects of the ETS. The central and western regions, especially the west, are more dependent on high-carbon industries, and governments are likely to be more aggressive in implementing the ETS, so the effect of the policy will be more pronounced in these regions.

Table 12. The regression results of regional heterogeneity analysis.

Variables	(1) CAE	(2) CAE	(3) CAE	(4) LAE	(5) LAE	(6) LAE
<i>DIDs</i>	0.1576 (0.1997)	−0.1287 *** (0.0240)	−0.0867 *** (0.0215)	−0.0499 (0.0741)	0.0067 (0.0285)	0.0591 ** (0.0216)
Constant	0.2822 ** (0.0980)	0.2365 *** (0.0134)	0.3368 *** (0.0078)	0.3458 *** (0.0294)	−0.1067 *** (0.0145)	−0.2366 *** (0.0087)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110	80	110	110	80	110
R-squared	0.2813	0.2349	0.2416	0.4941	0.4424	0.1036

Standard errors are in parentheses; **, and *** indicate the significance at the 5%, and 1% levels, respectively.

4.4.2. Carbon Emissions

As shown in Figure 5, a map based on the average carbon emissions of each province between 2011 and 2020 was created. Based on this map, the samples were categorized into three distinct emission zones: low, medium, and high carbon. Qinghai, Tianjin, Beijing, and other regions were included in the low-carbon emission zone; Heilongjiang, Xinjiang, and other regions were included in the medium-carbon emission zone; and Inner Mongolia, Hebei, Shandong, and other regions were included in the high-carbon emission zone. Grouped regression was carried out, and Table 13 shows the outcomes.

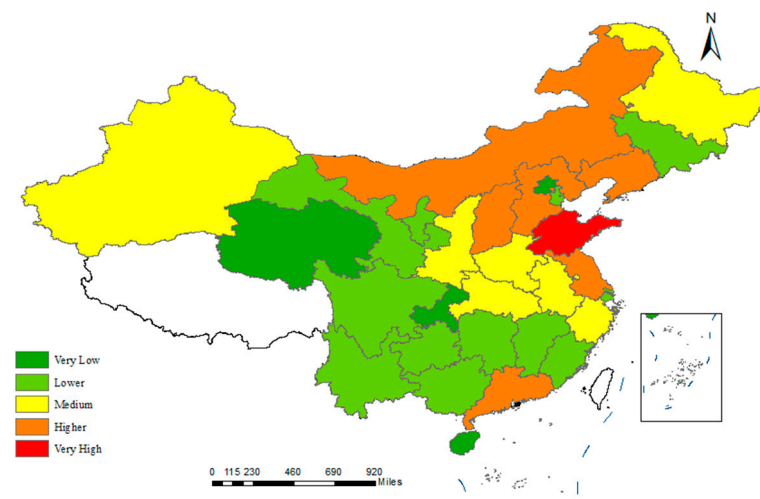


Figure 5. Carbon emissions distribution map.

Table 13. The regression results of carbon emissions heterogeneity analysis.

Variables	(1) CAE	(2) CAE	(3) CAE	(4) LAE	(5) LAE	(6) LAE
<i>DIDs</i>	−0.0436 (0.1268)	−0.1273 *** (0.0114)	0.0788 *** (0.0104)	0.0256 (0.0369)	0.0035 (0.0057)	−0.1089 ** (0.0441)
Constant	0.1873 (0.1167)	0.2450 *** (0.0124)	0.1885 *** (0.0124)	−0.0262 (0.0298)	0.0429 * (0.0202)	0.2184 *** (0.0449)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160	70	70	160	70	70
R-squared	0.3610	0.8744	0.9304	0.5492	0.5977	0.7694

Standard errors are in parentheses; *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively.

Low- and medium-carbon emission zones can help maximize capital allocation efficiency, but they do not support the improvement of labor allocation. However, high carbon emission zones encourage the increase in labor allocation efficiency but do not optimize capital allocation efficiency. The possible reason is that low-carbon emission zones and medium carbon emission zones tend to pay greater attention to the development of green technologies and environmental protection industries, which frequently require higher capital investment for research development and innovation. Concurrently, the government might offer incentives such as tax benefits and subsidies to draw more capital into these domains, thereby optimizing the allocation of capital. And these areas are typically accompanied by the transformation and upgrading of the industrial structure, and traditional industries with high energy consumption and high emissions might gradually withdraw or undergo technological transformation. During this process, a portion of the labor force might encounter employment challenges due to skill mismatches or job reduction, influencing the labor allocation efficiency. High carbon emission areas frequently confront greater

environmental pressure and risks, encompassing escalating pollution control costs and tightening environmental regulations. These factors might augment the operating costs of enterprises, diminish the return on investment, and thus impact the capital allocation efficiency. Concurrently, these areas are often dominated by traditional industries, which might possess certain stability and continuity in labor demand. For a workforce with relevant skills, these industries provide relatively stable employment opportunities.

5. Synergistic Effect

The ETS aims to promote the reduction of carbon emissions through economic incentives as a market-oriented environmental policy tool, so as to optimize resource allocation. However, the effective operation of the market mechanism often requires the reasonable guidance and support of government intervention to overcome market failures, ensure fair competition, and promote the realization of policy. Therefore, when studying the impact of the ETS on the efficiency of resource allocation, it is particularly important to explore the synergistic mechanism between market mechanism and government intervention.

5.1. Market Mechanism

Table 14 displays the results of the regression of model (4). When the carbon price is used to measure the market mechanism, the interaction term coefficient is significant at the level of 5% for both capital allocation efficiency and labor allocation efficiency, and the DIDs coefficient is significant at the level of 1%. This shows that the carbon price can significantly affect the optimization effect of the ETS on resource allocation efficiency. When the market mechanism is measured by market transaction amount, the DIDs coefficient is only significant when measuring labor allocation efficiency, which means that the carbon market promotes the optimization of the capital allocation efficiency through channels other than the market mechanism. The scale of the market transaction can promote the optimization of labor allocation efficiency in the carbon market, but the carbon market still significantly affects the efficiency of resource allocation through channels other than the market mechanism.

Table 14. The regression results of regional heterogeneity analysis.

Variables	(1) CAE	(2) CAE	(3) LAE	(4) LAE
<i>DIDs</i>	−0.2646 *** (0.0522)	−0.1994 *** (0.0622)	0.0648 *** (0.0193)	0.0450 *** (0.0114)
<i>price</i>	0.0034 ** (0.0013)		−0.0013 ** (0.0006)	
<i>amount</i>		0.0720 (0.0534)		−0.0595 ** (0.0284)
Constant	0.5631 (1.5232)	0.8578 (1.5239)	−0.3508 (0.7459)	−0.4279 (0.7848)
Control	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	300	300	300	300
R-squared	0.7137	0.6994	0.6970	0.6911

Standard errors are in parentheses; **, and *** indicate the significance at the 5%, and 1% levels, respectively.

The carbon market has a significant effect on the optimization of capital allocation efficiency in pilot areas, which is mainly due to the market mechanism with carbon emission trading system as the core, especially the direct impact of the carbon price. However, despite the fact that the market mechanism is important, the overall effectiveness of it is still insufficient due to the limited scale of market transactions. At the same time, non-market mechanisms also play a key role in improving the efficiency of resource allocation. This indicates that in the process of building and perfecting the carbon market, we should pay

attention to the deep integration of the market mechanism and the non-market mechanism to achieve the synergistic effect of the two. The government should take this opportunity to encourage enterprises to strengthen technological innovation, personnel training, and information construction, by formulating supporting policies, so as to further improve the efficiency of resource allocation.

5.2. Government Intervention

Table 15 displays the results of the regression of model (5). It was found that the high proportion of state-owned enterprises poses a challenge to the carbon market in improving the efficiency of labor allocation, and the rigidity of their internal management slows down the speed of labor market adjustment and affects the adaptability to changes in the carbon market. This highlights the importance of state-owned enterprise reform to enhance its market flexibility and responsiveness. At the same time, when the government takes intense punishment measures, the impact of the ETS on the efficiency of the capital allocation is significantly enhanced, indicating that government intervention has a complementary role when the market mechanism is immature, and can promote the effective use of resources. However, this emphasizes that on the premise of respecting the law of the market, the government should promote the improvement of the market mechanism through reasonable policy guidance and support, rather than replacing the market. In addition, the carbon market in the pilot area is in its early stage, and the market mechanism is not yet perfect, which limits its potential for optimizing resource allocation. Therefore, in the early stage of development, the leading role of the government is crucial, and it is necessary to lay a solid foundation for the steady development of the carbon market through policy support, system construction, and market supervision.

Table 15. The regression results of regional heterogeneity analysis.

Variables	(1) CAE	(2) CAE	(3) LAE	(4) LAE
<i>DIDs</i>	−0.1892 ** (0.0740)	−0.2972 *** (0.0542)	0.0866 *** (0.0161)	0.0568 ** (0.0276)
<i>staog</i>	0.0026 (0.1500)		−0.1505 *** (0.0479)	
<i>penalty</i>		0.0321 *** (0.0115)		−0.0062 (0.0070)
Control	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Constant	0.9555 (1.5345)	1.0135 (1.5069)	−0.4762 (0.7768)	−0.5201 (0.7897)
Observations	300	300	300	300
R-squared	0.6978	0.7041	0.6955	0.6869

Standard errors are in parentheses; **, and *** indicate the significance at the 5%, and 1% levels, respectively.

The carbon market can promote the optimization of capital allocation efficiency in pilot areas, but it is not conducive to the optimization of labor allocation efficiency. At present, the effect is limited, and government regulation can significantly improve the optimization effect of the carbon market. At present, the ETS market in China promotes the optimization of the resource allocation efficiency through the synergy effect of the market mechanism and government intervention. In addition, the carbon market in the pilot area started late, and the market mechanism was not yet mature. For the aforementioned mechanism to be realized in the early stages of development, the power of government involvement must be relied upon.

6. Conclusions and Policy Implications

Different from studies that have concentrated on the impact of the ETS on sustainability and green economic development [66–72], this paper explores the effect of the ETS on resource allocation efficiency using data from 30 Chinese provinces over the past decade. This research set up an experimental group including seven pilot areas to comprehensively evaluate the resource allocation efficiency by quantifying the capital and labor allocation efficiency, and built a DID model based on the panel data. This model aims to theoretically analyze how factors such as the ETS market, the carbon price, and the trading scale affect resource allocation efficiency in China, filling a gap in the research in this field. The results show that (1) within the pilot regions, the build of the ETS has effectively facilitated the enhancement of capital allocation efficiency. However, its performance in bolstering labor allocation efficiency remains modest, failing to meet the anticipated level of improvement. This suggests that while the ETS has a positive impact on capital allocation, its influence on labor markets is more nuanced and potentially constrained by other factors. (2) While the ETS market mechanism has contributed to improving both capital and labor allocation efficiency, its impact is limited. Notably, government intervention has emerged as a more influential factor in shaping these effects. This underscores the importance of a balanced approach, where the market mechanism and government policies work in tandem to optimize resource allocation. (3) This study further reveals that the impact of the ETS varies significantly across geographical regions. In the eastern region, the ETS does not significantly affect either capital or labor allocation efficiency. Conversely, in the central and western regions, the ETS has a notable positive effect on capital allocation efficiency. Notably, in the central region, the impact on labor allocation efficiency is not statistically significant, indicating that the effects of the ETS on labor markets may be more localized or contingent upon specific regional characteristics.

Based on these findings, policy recommendations should focus on strengthening the ETS in regions where it has shown positive impacts on capital allocation efficiency, while addressing the constraints that limit its influence on labor markets; developing region-specific policies that account for the unique characteristics and challenges faced by different regions; promoting a balanced approach that integrates market mechanisms and government intervention to optimize resource allocation across all regions. These policy recommendations provide a solid foundation based on the experimental results and their implications for resource allocation efficiency:

1. Enhancing ETS transparency and accountability: To further bolster the effectiveness of the Emission Trading System (ETS) in regions where it has proven beneficial, it is crucial to enhance the transparency and accountability mechanisms. This includes regular audits of the emissions data, public disclosure of trading activities, and the establishment of independent oversight bodies to ensure compliance and prevent market manipulation;

2. Addressing labor market constraints: Recognizing that the ETS may not uniformly influence labor markets, targeted interventions are needed to mitigate any adverse effects. This could involve providing retraining programs for workers displaced by the transition to a low-carbon economy, offering subsidies or tax incentives for businesses that hire such workers, and developing comprehensive employment strategies that align with regional economic development goals. Additionally, promoting flexibility in work arrangements and supporting the development of new industries and sectors that can absorb labor market shifts will be key;

3. Customizing policies: Tailored policies are crucial due to regional diversity. Fossil fuel-dependent regions need support for diversification, while renewable-rich regions require policies to boost investment and innovation. Robust analysis and stakeholder engagement ensure local responsiveness. Regional policy councils can aid this by gathering officials, business leaders, and community reps;

4. Cross-regional collaboration: Collaboration can share best practices, leverage scale, and address challenges. This includes regional carbon markets, R&D partnerships, and

coordinated infrastructure projects. Cooperation avoids duplication, pools resources, and enhances efficiency;

5. Market and government balance: Combining market mechanisms and government intervention optimizes resource allocation. The ETS incentivizes cleaner technologies, while the government sets targets, funds green projects, and regulates high-impact industries. Clear regulations encourage long-term business investments.

Natural disasters and changes in the global economy have profoundly affected the ETS and the efficiency of resource allocation. Natural disasters, such as earthquakes and floods, have a direct impact on ETS operations, resulting in an imbalance between supply and demand for emission allowances, increased volatility in carbon prices, and increased market uncertainty. At the same time, the disaster affected the enforcement of regulators, adding to the market chaos. Market participants, faced with disaster uncertainty, adopt conservative strategies, reduce transactions, reduce market liquidity, and affect the ETS's price discovery and resource allocation functions. The COVID-19 outbreak in 2019 has had a profound impact on global ETS. In the case of the EU ETS, for example, in the face of the pandemic shock, the system quickly adapted its strategy to the changes. On the one hand, in order to mitigate the impact of the epidemic on the economy, the EU ETS has suspended some quota auctions, reducing the burden of emissions costs for enterprises. On the other hand, the EU ETS has enhanced the flexibility of data reporting and verification, allowing companies to delay their submission of emissions data due to the operational disruptions caused by the pandemic. The impact of global economic changes on the ETS is more complex, including global economic recession, trade wars, etc., affecting the international carbon emission rights trading, changing national climate policies, and weakening the international synergy of the ETS. Changes in multinational investment strategies by companies and investors may increase the risk of carbon leakage and weaken the efficiency of ETS resource allocation.

There are some limitations in this paper. Firstly, the research period was from 2011 to 2020. At the same time, COVID-19's influence on the economy cannot be ruled out. Secondly, there might have been biases in the sample selection process related to the time periods or provinces. These biases may have had an impact on how accurate the study's findings are. The sample, for instance, includes a number of developed provinces that, even before the introduction of CTPP, had superior resource allocation efficiency. As a result, these provinces may perform more noticeably following the implementation of CTPP. This could result in an overemphasis on how CTPP improves resource allocation efficiency. In addition, policy changes may not take effect all at once, and the results could be inaccurate if these time lag effects were not taken into consideration.

While multi-period DID models are capable of capturing variations in ETS implementation across pilot regions, they may not adequately address potential interactions between the ETS and other policies. Additionally, this study did not delve into the resource allocation efficiency within specific sectors or industries, notably the service industry, which presents an avenue for future research. Potential future research endeavors in related fields should include, but are not limited to, refining the impact of carbon trading on resource allocation efficiency across different industries and regions; exploring the synergies between carbon trading and other environmental and economic policies; and evaluating the long-term impact of carbon trading policies on resource allocation efficiency and sustainable development. By conducting these studies, a more comprehensive understanding of the implementation effects of carbon trading policies can be gained, thereby providing a more scientific basis for policymakers to foster green transformation and sustainable development of the economy and society.

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References

1. Hong, Q.Q.; Cui, L.H.; Hong, P.H. The impact of carbon emissions trading on energy efficiency: Evidence from quasi-experiment in China's carbon emissions trading pilot. *Energy Econ.* **2022**, *110*, 106025. [\[CrossRef\]](#)
2. Cheng, Y.W.; Mu, D.; Ren, H.Y.; Fan, T.J.; Du, J.B. Using a temporal input-output approach to analyze the ripple effect of China's energy consumption. *Energy* **2020**, *211*, 118641. [\[CrossRef\]](#)
3. Liu, L.C.; Cao, D.; Wei, Y.M. What drives intersectoral CO₂ emissions in China? *J. Clean. Prod.* **2016**, *133*, 1053–1061. [\[CrossRef\]](#)
4. Zheng, G.; Barbieri, E.; Di Tommaso, M.R.; Zhang, L. Development zones and local economic growth: Zooming in on the Chinese case. *China Econ. Rev.* **2016**, *38*, 238–249. [\[CrossRef\]](#)
5. Huang, H.P.; Yi, M.T. Impacts and mechanisms of heterogeneous environmental regulations on carbon emissions: An empirical research based on DID method. *Environ. Impact Assess. Rev.* **2023**, *99*, 107039. [\[CrossRef\]](#)
6. Wu, J.X.; Nie, X.; Wang, H. Curse to blessing: The carbon emissions trading system and resource-based cities' carbon mitigation. *Energy Policy* **2023**, *183*, 113796. [\[CrossRef\]](#)
7. Jiang, J.J.; Xie, D.J.; Ye, B.; Shen, B.; Chen, Z.M. Research on China's cap-and-trade carbon emission trading scheme: Overview and outlook. *Appl. Energy* **2016**, *178*, 902–917. [\[CrossRef\]](#)
8. Lv, M.C.; Bai, M.Y. Evaluation of China's carbon emission trading policy from corporate innovation. *Financ. Res. Lett.* **2021**, *39*, 101565. [\[CrossRef\]](#)
9. Cui, J.B.; Wang, C.H.; Zhang, J.J.; Zheng, Y. The effectiveness of China's regional carbon market pilots in reducing firm emissions. *Proc. Natl. Acad. Sci. USA* **2021**, *118*, e2109912118. [\[CrossRef\]](#)
10. Wei, Y.M.; Du, M.Z.; Huang, Z.X. The effects of energy quota trading on total factor productivity and economic potential in industrial sector: Evidence from China. *J. Clean. Prod.* **2024**, *445*, 141227. [\[CrossRef\]](#)
11. Lin, B.Q.; Huang, C.C. Analysis of emission reduction effects of carbon trading: Market mechanism or government intervention? *Sustain. Prod. Consum.* **2022**, *33*, 28–37. [\[CrossRef\]](#)
12. Jia, Z.J.; Lin, B.Q. Rethinking the choice of carbon tax and carbon trading in China. *Technol. Forecast. Soc. Chang.* **2020**, *159*, 120187. [\[CrossRef\]](#)
13. Li, X.; Li, Z.; Su, C.W.; Umar, M.; Shao, X.F. Exploring the asymmetric impact of economic policy uncertainty on China's carbon emissions trading market price: Do different types of uncertainty matter? *Technol. Forecast. Soc. Chang.* **2022**, *178*, 121601. [\[CrossRef\]](#)
14. Tang, H.L.; Liu, J.M.; Wu, J.G. The impact of command-and-control environmental regulation on enterprise total factor productivity: A quasi-natural experiment based on China's "Two Control Zone" policy. *J. Clean. Prod.* **2020**, *254*, 120011. [\[CrossRef\]](#)
15. Narassimhan, E.; Gallagher, K.S.; Koester, S.; Alejo, J.R. Carbon pricing in practice: A review of existing emissions trading systems. *Clim. Policy* **2018**, *18*, 967–991. [\[CrossRef\]](#)
16. Cael, R.; Dechezleprêtre, A. Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market. *Rev. Econ. Stat.* **2016**, *98*, 173–191. [\[CrossRef\]](#)
17. Pietzcker, R.C.; Osorio, S.; Rodrigues, R. Tightening EU ETS targets in line with the European Green Deal: Impacts on the decarbonization of the EU power sector. *Appl. Energy* **2021**, *293*, 116914. [\[CrossRef\]](#)
18. Dechezleprêtre, A.; Nachtigall, D.; Venmans, F. The joint impact of the European Union emissions trading system on carbon emissions and economic performance. *J. Environ. Econ. Manag.* **2023**, *118*, 102758. [\[CrossRef\]](#)
19. Aguiar-Conraria, L.; Soares, M.J.; Sousa, R. California's carbon market and energy prices: A wavelet analysis. *Philos. Trans. R. Soc. A-Math. Phys. Eng. Sci.* **2018**, *376*, 20170256. [\[CrossRef\]](#)
20. Xiong, L.; Shen, B.; Qi, S.Z.; Price, L.; Ye, B. The allowance mechanism of China's carbon trading pilots: A comparative analysis with schemes in EU and California. *Appl. Energy* **2017**, *185*, 1849–1859. [\[CrossRef\]](#)
21. Zhou, F.X.; Wang, X.Y. The carbon emissions trading scheme and green technology innovation in China: A new structural economics perspective. *Econ. Anal. Policy* **2022**, *74*, 365–381. [\[CrossRef\]](#)
22. Teixido, J.; Verde, S.F.; Nicolli, F. The impact of the EU Emissions Trading System on low-carbon technological change: The empirical evidence. *Ecol. Econ.* **2019**, *164*, 106347. [\[CrossRef\]](#)
23. Sun, H.P.; Edziah, B.K.; Kporsu, A.K.; Sarkodie, S.A.; Taghizadeh-Hesary, F. Energy efficiency: The role of technological innovation and knowledge spillover. *Technol. Forecast. Soc. Chang.* **2021**, *167*, 120659. [\[CrossRef\]](#)

24. Wang, H.; Chen, Z.P.; Wu, X.Y.; Niea, X. Can a carbon trading system promote the transformation of a low-carbon economy under the framework of the porter hypothesis?—Empirical analysis based on the PSM-DID method. *Energy Policy* **2019**, *129*, 930–938. [\[CrossRef\]](#)
25. Qiang, O.Y.; Wang, T.T.; Ying, D.; Li, Z.P.; Jahanger, A. The impact of environmental regulations on export trade at provincial level in China: Evidence from panel quantile regression. *Environ. Sci. Pollut. Res.* **2022**, *29*, 24098–24111. [\[CrossRef\]](#)
26. Marin, G.; Marino, M.; Pellegrin, C. The Impact of the European Emission Trading Scheme on Multiple Measures of Economic Performance. *Environ. Resour. Econ.* **2018**, *71*, 551–582. [\[CrossRef\]](#)
27. Loisel, R. Environmental climate instruments in Romania: A comparative approach using dynamic CGE modelling. *Energy Policy* **2009**, *37*, 2190–2204. [\[CrossRef\]](#)
28. Chen, P.S.; He, Y.; Yue, K.; Fang, G.C. Can Carbon Trading Promote Low-Carbon Transformation of High Energy Consumption Enterprises?—The Case of China. *Energies* **2023**, *16*, 3438. [\[CrossRef\]](#)
29. Zhou, Z.; Ma, Z.C.; Lin, X.W. Carbon emissions trading policy and green transformation of China's manufacturing industry: Mechanism assessment and policy implications. *Front. Environ. Sci.* **2022**, *10*, 984612. [\[CrossRef\]](#)
30. Yu, D.S.; Liu, L.X.; Gao, S.H.; Yuan, S.Y.; Shen, Q.L.; Chen, H.P. Impact of carbon trading on agricultural green total factor productivity in China. *J. Clean. Prod.* **2022**, *367*, 132789. [\[CrossRef\]](#)
31. Li, J.Q.; Huang, D.C.; Wu, X.Q. The Impact of China's Carbon Emission Trading Policy on Green Total Factor Productivity—Influence Analysis Based on Super-EBM and Multiple Mediators. *Pol. J. Environ. Stud.* **2022**, *31*, 5107–5123. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Yu, Z.H.; Mao, S.P.; Lin, Q.N. Has China's Carbon Emissions Trading Pilot Policy Improved Agricultural Green Total Factor Productivity? *Agriculture* **2022**, *12*, 1444. [\[CrossRef\]](#)
33. Xiao, Y.; Huang, H.; Qian, X.M.; Chen, L. Can carbon emission trading pilot facilitate green development performance? Evidence from a quasi-natural experiment in China. *J. Clean. Prod.* **2023**, *400*, 136755. [\[CrossRef\]](#)
34. Zeng, B.X.; Xie, J.; Zhang, X.B.; Yu, Y.; Zhu, L. The impacts of emission trading scheme on China's thermal power industry: A pre-evaluation from the micro level. *Energy Environ.* **2020**, *31*, 1007–1030. [\[CrossRef\]](#)
35. Zhang, Y.F.; Li, S.; Luo, T.Y.; Gao, J. The effect of emission trading policy on carbon emission reduction: Evidence from an integrated study of pilot regions in China. *J. Clean. Prod.* **2020**, *265*, 121843. [\[CrossRef\]](#)
36. Xuan, D.; Ma, X.W.; Shang, Y.P. Can China's policy of carbon emission trading promote carbon emission reduction? *J. Clean. Prod.* **2020**, *270*, 122383. [\[CrossRef\]](#)
37. Chen, X.; Lin, B.Q. Towards carbon neutrality by implementing carbon emissions trading scheme: Policy evaluation in China. *Energy Policy* **2021**, *157*, 112510. [\[CrossRef\]](#)
38. Zhang, W.; Li, J.; Li, G.X.; Guo, S.C. Emission reduction effect and carbon market efficiency of carbon emissions trading policy in China. *Energy* **2020**, *196*, 117117. [\[CrossRef\]](#)
39. Wu, M.; Li, K.X.; Xiao, Y.; Yuen, K.F. Carbon Emission Trading Scheme in the shipping sector: Drivers, challenges, and impacts. *Mar. Policy* **2022**, *138*, 104989. [\[CrossRef\]](#)
40. Liu, P.K.; Wu, J.H. Study on the diffusion of CCUS technology under carbon trading mechanism: Based on the perspective of tripartite evolutionary game among thermal power enterprises, government and public. *J. Clean. Prod.* **2024**, *438*, 140730. [\[CrossRef\]](#)
41. Hu, H.; Qi, S.Z.; Chen, Y.Z. Using green technology for a better tomorrow: How enterprises and government utilize the carbon trading system and incentive policies. *China Econ. Rev.* **2023**, *78*, 101933. [\[CrossRef\]](#)
42. Liu, B.L.; Ding, C.J.; Hu, J.; Su, Y.Q.; Qin, C. Carbon trading and regional carbon productivity. *J. Clean. Prod.* **2023**, *420*, 138395. [\[CrossRef\]](#)
43. Cao, K.Y.; Xu, X.P.; Wu, Q.; Zhang, Q.P. Optimal production and carbon emission reduction level under cap-and-trade and low carbon subsidy policies. *J. Clean. Prod.* **2017**, *167*, 505–513. [\[CrossRef\]](#)
44. Liu, L.W.; Chen, C.X.; Zhao, Y.F.; Zhao, E.D. China's carbon-emissions trading: Overview, challenges and future. *Renew. Sustain. Energy Rev.* **2015**, *49*, 254–266. [\[CrossRef\]](#)
45. Hsieh, C.T.; Klenow, P.J. Misallocation and Manufacturing TFP in China and India. *Q. J. Econ.* **2009**, *124*, 1403–1448. [\[CrossRef\]](#)
46. Zuo, P.; Jiang, Q.; Chen, J. Internet Development, Urbanization and the Upgrading of China's Industrial Structure. *Quant. Tech. Econ.* **2020**, *37*, 71–91.
47. Qian, W.; Liu, H.; Pan, F.H. Digital Economy, Industry Heterogeneity, and Service Industry Resource Allocation. *Sustainability* **2022**, *14*, 8020. [\[CrossRef\]](#)
48. Zhu, W.J.; Huang, J.; Cai, N. Comparing the Digital Economy Urban Network: Study Based on the Human Resource Needs in the Yangtze River Delta, China. *J. Urban Plan. Dev.* **2022**, *148*, 05022033. [\[CrossRef\]](#)
49. Ning, J.; Yin, Q.R.; Yan, A. How does the digital economy promote green technology innovation by manufacturing enterprises? Evidence from China. *Front. Environ. Sci.* **2022**, *10*, 967588. [\[CrossRef\]](#)
50. Wang, G.; Zhang, G.; Guo, X.; Zhang, Y.F. Digital twin-driven service model and optimal allocation of manufacturing resources in shared manufacturing. *J. Manuf. Syst.* **2021**, *59*, 165–179. [\[CrossRef\]](#)
51. Zhang, W.; Li, G.X.; Guo, F.Y. Does carbon emissions trading promote green technology innovation in China? *Appl. Energy* **2022**, *315*, 119012. [\[CrossRef\]](#)

52. Shen, B.; Yang, X.D.; Xu, Y.; Ge, W.F.; Liu, G.L.; Su, X.F.; Zhao, S.K.; Dagestani, A.; Ran, Q.Y. Can carbon emission trading pilot policy drive industrial structure low-carbon restructuring: New evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 41553–41569. [[CrossRef](#)] [[PubMed](#)]
53. Wang, Y.F.; Liu, J.; Zhao, Z.H.; Ren, J.; Chen, X.R. Research on carbon emission reduction effect of China's regional digital trade under the double carbon target—Combination of the regulatory role of industrial agglomeration and carbon emissions trading mechanism. *J. Clean. Prod.* **2023**, *405*, 137049. [[CrossRef](#)]
54. Wang, B.; Yang, M.J.; Zhang, X. The effect of the carbon emission trading scheme on a firm's total factor productivity: An analysis of corporate green innovation and resource allocation efficiency. *Front. Environ. Sci.* **2022**, *10*, 1036482. [[CrossRef](#)]
55. Ma, J.J.; Xiang, Y.J.; Bai, X.W. Carbon emission trading scheme and corporate labor investment efficiency: Evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 90830–90843. [[CrossRef](#)] [[PubMed](#)]
56. Chen, S.Y.; Wang, C. Distributional employment impacts of the nationwide emission trading scheme in China. *J. Environ. Manag.* **2023**, *334*, 117526. [[CrossRef](#)]
57. Chen, Y.; Hu, W. Distortions, Misallocation and Losses: Theory and Application. *China Econ. Q.* **2011**, *10*, 1401–1422.
58. Sarkodie, S.A.; Strezov, V. Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. *Sci. Total Environ.* **2019**, *646*, 862–871. [[CrossRef](#)]
59. Aust, V.; Morais, A.I.; Pinto, I. How does foreign direct investment contribute to Sustainable Development Goals? Evidence from African countries. *J. Clean. Prod.* **2020**, *245*, 118823. [[CrossRef](#)]
60. Yang, Y.P.; Wu, D.; Xu, M.; Yang, M.T.; Zou, W.J. Capital misallocation, technological innovation, and green development efficiency: Empirical analysis based on China provincial panel data. *Environ. Sci. Pollut. Res.* **2022**, *29*, 65535–65548. [[CrossRef](#)]
61. Long, H.L.; Tu, S.S.; Ge, D.Z.; Li, T.T.; Liu, Y.S. The allocation and management of critical resources in rural China under restructuring: Problems and prospects. *J. Rural Stud.* **2016**, *47*, 392–412. [[CrossRef](#)]
62. Wu, Y.; Qi, J.; Xian, Q.; Chen, J.D. The Carbon Emission Reduction Effect of China's Carbon Market—From the Perspective of the Coordination between Market Mechanism and Administrative Intervention. *China Ind. Econ.* **2021**, *8*, 114–132.
63. Jin, W.; Zhang, H.Q.; Liu, S.S.; Zhang, H.B. Technological innovation, environmental regulation, and green total factor efficiency of industrial water resources. *J. Clean. Prod.* **2019**, *211*, 61–69. [[CrossRef](#)]
64. Bertrand, M.; Duflo, E.; Mullainathan, S. How much should we trust differences-in-differences estimates? *Q. J. Econ.* **2004**, *119*, 249–275. [[CrossRef](#)]
65. Chetty, R.; Looney, A.; Kroft, K. Salience and Taxation: Theory and Evidence. *Am. Econ. Rev.* **2009**, *99*, 1145–1177. [[CrossRef](#)]
66. Bauer, N.; Bosetti, V.; Hamdi-Cherif, M.; Kitous, A.; McCollum, D.; Mejean, A.; Rao, C.S.; Turton, H.; Paroussos, L.; Ashina, S.; et al. CO₂ emission mitigation and fossil fuel markets: Dynamic and international aspects of climate policies. *Technol. Forecast. Soc. Chang.* **2015**, *90*, 243–256. [[CrossRef](#)]
67. Chen, Y.L.; Wang, Z.; Zhong, Z.Q. CO₂ emissions, economic growth, renewable and non-renewable energy production and foreign trade in China. *Renew. Energy* **2019**, *131*, 208–216. [[CrossRef](#)]
68. Chepeliev, M.; Osorio-Rodarte, I.; van der Mensbrugghe, D. Distributional impacts of carbon pricing policies under the Paris Agreement: Inter and intra-regional perspectives. *Energy Econ.* **2021**, *102*, 105530. [[CrossRef](#)]
69. Dou, X.S. Low Carbon-Economy Development: China's Pattern and Policy Selection. *Energy Policy* **2013**, *63*, 1013–1020. [[CrossRef](#)]
70. Tan, X.J.; Choi, Y.; Wang, B.B.; Huang, X.Q. Does China's carbon regulatory policy improve total factor carbon efficiency? A fixed-effect panel stochastic frontier analysis. *Technol. Forecast. Soc. Chang.* **2020**, *160*, 120222. [[CrossRef](#)]
71. Wang, M.X.; Zhao, R.D.; Li, B. Impact of financing models and carbon allowance allocation rules in a supply chain. *J. Clean. Prod.* **2021**, *302*, 126794. [[CrossRef](#)]
72. Chen, S.; Shi, A.N.; Wang, X. Carbon emission curbing effects and influencing mechanisms of China's Emission Trading Scheme: The mediating roles of technique effect, composition effect and allocation effect. *J. Clean. Prod.* **2020**, *264*, 121700. [[CrossRef](#)]

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