China's Pilot Carbon Market: Institutional Design for Industrial Low-Carbon Transition

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Abstract: *This study explores the mechanisms by which China's pilot carbon emissions trading schemes (ETS) facilitate industrial low-carbon transitions. We construct a theoretical model and conduct an empirical analysis using provincial panel data from seven pilot provinces spanning 2006-2021. Applying a multi-period difference-in-differences (DID) approach, we evaluate the environmental and economic impacts of the pilot ETS policies. The findings yield three key insights: (1) The pilot ETS significantly reduces carbon emission intensity and improves low-carbon total factor productivity (TFP), thereby promoting China's industrial low-carbon transition. (2) Mechanism analysis indicates that the ETS primarily operates through cost constraints and industrial structural upgrading, while the effect of technological progress has yet to fully materialize. (3) Heterogeneity analysis reveals that the policy's effects are more significant in regions with higher levels of economic development and R&D investment, leading to greater carbon intensity reductions and productivity gains. In addition, regions with higher foreign direct investment (FDI) experience more substantial improvements in low-carbon TFP, possibly reflecting technology spillover effects.*

Keywords: *Pilot carbon emissions trading scheme; Industrial low-carbon transition; National unified carbon market; Carbon emission intensity; Low-carbon total factor productivity*

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1. Introduction

For decades, industry has powered China's rapid economic growth, driving its economic restructuring efforts. Since the early 21st century, the conflict between industrial development and environmental protection has become increasingly apparent. Heavy reliance on fossil fuels has led to high levels of emissions, contributing to climate change and environmental degradation. These challenges have made it imperative for China to transform its development model and pursue high-quality growth under a new development paradigm. In recent years, driven by growing environmental policy constraints, China's development agenda has increasingly centered on a new path to industrialization, energy efficiency improvements, and emissions reductions. Against this backdrop, the carbon emissions trading market, or "carbon market", emerged. Pilot ETS programs were launched

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in Beijing, Shanghai, Tianjin, and Guangdong in 2013, followed by Hubei and Chongqing in 2014, and Fujian in 2016. These pilot programs have become key instruments for achieving China's "carbon peaking and neutrality" goals—peaking carbon emissions by 2030 and reaching carbon neutrality by 2060—and have laid the foundation for a unified national carbon market. In 2017, the 19th National Congress of the Communist Party of China (CPC) designated the construction of an ecological civilization as a "millennium strategy", marking a major shift that placed green development at the heart of the national development agenda. In 2022, the 20th CPC National Congress reinforced its commitment to proactive yet prudent carbon peaking and neutrality, promoting clean, low-carbon energy use and advancing low-carbon transitions in industry, construction, and transportation. In this context, examining the pilot carbon market's impact on industrial low-carbon transition offers timely insights into China's evolving growth model and provides empirical support for effective policy implementation.

This paper makes three key contributions. First, it introduces a new theoretical perspective on industrial low-carbon transition by focusing on the pilot carbon trading policy. We construct a quasi-natural experimental setting to evaluate the impact of pilot ETS programs on industrial decarbonization, examining how industries can achieve both emission reductions and efficiency gains. We also explore regional and sectoral differences in the transition process under the constraints of the carbon market and emission reduction targets. Second, we apply a multi-period *difference-in-differences (DID)* method for policy evaluation, contributing to the growing body of literature on the impact of carbon trading schemes on industrial transformation. Third, we investigate the mechanisms through which the pilot carbon market influences industrial decarbonization, focusing on cost constraints, structural upgrading, and technological progress. The findings provide actionable policy recommendations to support industrial low-carbon transition and advance China's carbon peaking and neutrality goals.

2. Literature Review

Since the launch of China's pilot carbon emissions trading schemes (ETS), scholars have extensively examined their impacts, which can be broadly categorized into two strands: environmental effects and economic effects.

The first strand focuses on environmental outcomes, particularly whether pilot ETS reduce carbon emissions and emission intensity. Most studies find that the ETS has had a significant emission reduction effect and strong mitigation potential. For example, Zhang et al. (2017) reported that total carbon emissions from 635 industrial enterprises in Shenzhen declined by 11% from 2010 to 2015, indicating the emerging effectiveness of market mechanisms in promoting decarbonization. Li & Zhang (2017) identified key influencing factors—such as energy intensity, emission coefficients, and energy consumption structure—and used a stochastic frontier analysis (SFA) model to examine how the ETS improves energy and technical efficiency and allocative efficiency. Li (2021) demonstrated the existence of spatial emission reduction effects resulting from the pilot policy. Wu et al. (2021) constructed a theoretical model of synergy between market mechanisms and administrative interventions, analyzing both the theoretical logic and empirical evidence of their combined impact on emission reduction. Wang et al. (2022) reached similar conclusions. Cheng & Yang (2023), using panel data from 30 provinces, also confirmed the carbon mitigation effects of pilot ETS and further examined mediating channels such as green technological innovation and energy structure transformation.

The second strand of research explores economic effects, with a particular emphasis on total factor productivity (TFP). Many studies suggest that the pilot ETS has a positive impact on green or low-carbon TFP, thereby contributing to sustainable economic growth (Dong & Wang, 2021; Sun et al., 2022; Jia et al., 2022; Hu et al., 2023). This has important implications for promoting high-quality and green development (Jing, 2022; Zheng & Yao, 2023). Other research has examined the effects of the pilot ETS on industrial structure, energy efficiency, technological innovation, and corporate value. Regarding industrial structure, Tan & Zhang (2018), Liu & Cheng (2022), among others, argue that the carbon market reshapes firms' cost-benefit dynamics. To offset the cost pressures of environmental compliance, firms adjust factor allocation, product mix, and technology strategies, thereby driving structural upgrading at the macro level. In terms of energy efficiency, ETS facilitate more efficient allocation of resources and production factors, allowing cleaner and more efficient firms to thrive, thus encouraging green technological progress and improvements in overall energy use efficiency (Zhu & Sun, 2022).

In the area of technological innovation, existing research has shown that carbon trading policies can transmit expectations to firms through a "signal-anticipation" mechanism even before their official implementation, thereby encouraging firms to engage in low-carbon technological innovation (Wang et al., 2020). These innovations include technologies that achieve lower carbon emissions, zero-emission non-negative carbon technologies, and negative-carbon technologies that offset necessary emissions during production processes (Cao & Su, 2023), all of which help enterprises reduce expenditures on purchasing carbon quota or generate income by selling surplus quota. In terms of corporate value, carbon credit is regarded as a form of property right—an asset with both tangible and option value. Firms with lower carbon intensity often possess surplus allowances and face lower marginal abatement costs, enabling them to profit and realize value appreciation (Shen & Huang, 2019). Furthermore, research has found that carbon trading policies significantly enhance overall economic welfare (Zhang & Wang, 2022).

Despite these insights, important questions remain underexplored:

(1) Can pilot ETS effectively promote the low-carbon transition of the industrial sector?

(2) Are there differences in policy effects between pilot and non-pilot regions?

(3) How do the impacts vary across regions and industrial sectors?

(4) How can the ETS be further optimized to support industrial transformation?

Addressing these questions holds both theoretical and practical significance for understanding China's industrial development, evaluating ETS policy effectiveness, and informing strategies to achieve the "carbon peaking and neutrality" goals. This paper investigates the relationship between pilot ETS policies and industrial low-carbon transition, aiming to provide empirical evidence for improving carbon governance and supporting industrial modernization.

3. Theoretical Analysis and Hypotheses

Drawing upon the research frameworks of Deng & Yang (2019) and Wen & Liu (2022), this paper constructs a theoretical model incorporating carbon pricing, technological progress, and industrial structural adjustment. The model is designed to analyze the mechanisms through which the pilot carbon market influences the industrial low-carbon transition. Assume a region with two production sectors: X and Y. Sector X produces product x and generates carbon emissions z during its production process. Sector Y produces a clean product y, whose production involves no carbon emissions. Let the price of product x be p, and the price of product y be normalized to 1. Both sectors employ capital (K) and labor (L), with their respective factor prices denoted by r (capital) and w (labor). The production functions for both products are specified in the Cobb-Douglas (C-D) form, as follows for product $\boldsymbol{x}$ and product y, respectively:

$$F(K_x, L_x)=K_x^{\beta} L_x^{1-\beta} \tag{1}$$

$$F(K_y, L_y)=K_y^{\delta} L_y^{1-\delta} \tag{2}$$

In the absence of environmental regulations, the output of product x is directly proportional to carbon emissions z. However, under environmental regulatory pressure, firms must allocate a portion of their production factors, denoted by θ, to carbon emission control efforts ($\theta \in [0,1]$). As a result, the production functions for product x and carbon emissions z are, respectively, as follows:

$$x=F((1-\theta)K_x, (1-\theta)L_x)=(1-\theta)K_x^{\beta} L_x^{1-\beta} \tag{3}$$

$$z=\varphi(\theta)F(K_x, L_x)=\varphi(\theta)K_x^{\beta} L_x^{1-\beta} \tag{4}$$

Where $\varphi(\theta)$ is a decreasing function of θ, reflecting the level of carbon emission governance. Let $\varphi(\theta)=A^{-1}(1-\theta)^{1/\alpha}$, where A denotes the level of production technology, with $\alpha\in(0,1)$. At this point, the new expression for product x can be derived as:

$$x=(Az)^{\alpha}F^{1-\alpha} \tag{5}$$

Without considering environmental regulations, firms in sector X, like those in sector Y, aim to minimize costs according to equations (1) and (2), i.e.,

$$c_x^F(w, r)=\min\{rK_x+wL_x, F(K_x, L_x)=1\} \tag{6}$$

$$c_y^F(w, r)=\min\{rK_y+wL_y, F(K_y, L_y)=1\} \tag{7}$$

Let $M=(1-\beta)^{\beta-1}/\beta^{\beta}$ and $N=(1-\delta)^{\delta-1}/\delta^{\delta}$. Then, the average production costs of the two products are, respectively:

$$C_x=Mr^{\beta}w^{1-\beta} \tag{8}$$

$$C_y=Nr^{\delta}w^{1-\delta} \tag{9}$$

Assume that all carbon emissions z from sector X are traded in the carbon market, with the carbon price pt determined by market supply and demand. The cost minimization problem for firms in sector X then becomes:

$$c^x(c^F, p_t)=\min\{p_t Az+c^F F, (Az)^{\alpha}F^{1-\alpha}=1\} \tag{10}$$

The solution is: $p_t/c^F=\alpha F/(1-\alpha)Az$ (11)

Assume a perfectly competitive market in which firms satisfy the zero-profit condition, i.e.,

$$px=c^F F+p_t Az \tag{12}$$

Substituting equation (11) and simplifying yields: $z=\alpha px/Ap_t$ (13)

Furthermore, carbon emission intensity can be expressed as: $\frac{z}{px+y}=\frac{1}{p_t}*\frac{\alpha}{A}*\frac{px}{px+y}$ (14)

As shown in equation (14), under the constraints of the pilot carbon market, carbon emission intensity is jointly determined by three key factors: the carbon price, technological progress, and adjustments in industrial structure.

In a competitive market, the price of each commodity equals its production cost. From equations (3)-(4), (8)-(9), and (12), we obtain $Mr^{\beta}w^{1-\beta}=P=p(1-\theta)-p_t(1-\theta)^{1-\alpha}$, $Nr^{\delta}w^{1-\delta}=1$. Then, the factor prices can be derived as:

$$w=\left(\frac{1}{N}\right)^{\frac{\beta}{\beta-\delta}}\left(\frac{M}{P}\right)^{\frac{\delta}{\beta-\delta}}, r=\left(\frac{1}{N}\right)^{\frac{1-\beta}{\delta-\beta}}\left(\frac{M}{P}\right)^{\frac{1-\delta}{\delta-\beta}} \tag{15}$$

According to Shepherd's Lemma, the input demands per unit of products x and y can be determined, and the total factor input is given by:

$$L=L_x x+L_y y=M(1-\beta)r^{\beta}w^{-\beta}x+N(1-\delta)r^{\delta}w^{-\delta}y \tag{16}$$

$$K=K_x x+K_y y=M\beta r^{\beta-1}w^{1-\beta}x+N\delta r^{\delta-1}w^{1-\delta}y \tag{17}$$

The equilibrium outputs of sectors X and Y are then:

$$x=\frac{\left(\frac{\delta L}{1-\delta}\frac{w}{r}-K\right)}{\left(\frac{\delta-\beta}{1-\delta}M\left(\frac{w}{r}\right)^{1-\beta}\right)}, y=\frac{\left(\frac{\beta L}{1-\beta}\frac{w}{r}-K\right)}{\left(\frac{\beta-\delta}{1-\beta}N\left(\frac{w}{r}\right)^{1-\delta}\right)} \tag{18}$$

From equation (15), we have $\frac{w}{r}=SP^{1/(\delta-\beta)}$, and parameter $S=\left(\frac{M}{N}\right)^{1/(\beta-\delta)}$. Taking the derivative of equation (18) with respect to the carbon price p_t allows us to observe the impact of the pilot carbon market on the equilibrium outputs of the two products:

$$\frac{\partial x}{\partial p_t}=\frac{\partial x}{\partial P}\frac{\partial P}{\partial p_t}=\frac{\delta\beta S^{\beta}P^{\frac{\beta}{\delta-\beta}-1}L+(1-\delta)(1-\beta)S^{\beta-1}P^{\frac{\beta-1}{\delta-\beta}-1}}{(\beta-\delta)^2 M}\frac{\partial P}{\partial p_t}<0 \tag{19}$$

$$\frac{\partial y}{\partial p_t}=\frac{\partial y}{\partial P}\frac{\partial P}{\partial p_t}=\frac{\delta\beta S^{\delta}P^{\frac{\beta}{\delta-\beta}}L+(1-\delta)(1-\beta)S^{\delta-1}P^{\frac{\beta-1}{\delta-\beta}}K}{(\beta-\delta)^2 N}\frac{\partial P}{\partial p_t}>0 \tag{20}$$

Furthermore, this paper measures production efficiency by the ratio of the total output of the two sectors to the total factor input:

$$PE=\frac{\sum\lambda_i y_i}{\sum\mu_j I_j}=\frac{\lambda_1 x+\lambda_2 y}{\mu_1 L+\mu_2 K} \tag{21}$$

Let λ_i and μ_j denote the proportions of the i^{th} output and the j^{th} input, respectively. Then, the impact of the pilot carbon market on production efficiency is:

$$\frac{\partial PE}{\partial p_t}=\frac{1}{f}\left(\lambda_1\frac{\partial x}{\partial p_t}+\lambda_2\frac{\partial y}{\partial p_t}\right) \tag{22}$$

From equation (22), combined with (19) and (20), it is evident that the market mechanism can influence industrial structure adjustment by reducing the production of carbon-intensive products and increasing the output of cleaner products, thereby affecting regional production efficiency. Given a region's fixed factor endowments f, improvements in technological progress can also influence economic output via market mechanisms $\partial P/\partial p_t=-(1-\theta)^{\frac{1}{\alpha}}=-A\varphi(\theta)$, thereby enhancing production efficiency. Therefore, the pilot carbon market can influence both industrial structure and technological progress by imposing cost constraints through its price mechanism, which in turn affects production efficiency. Based on this, the paper argues that the pilot carbon market promotes low-carbon transition by imposing cost constraints, encouraging structural upgrading, and incentivizing technological innovation in industrial sectors. The specific mechanism is illustrated in Figure 1.

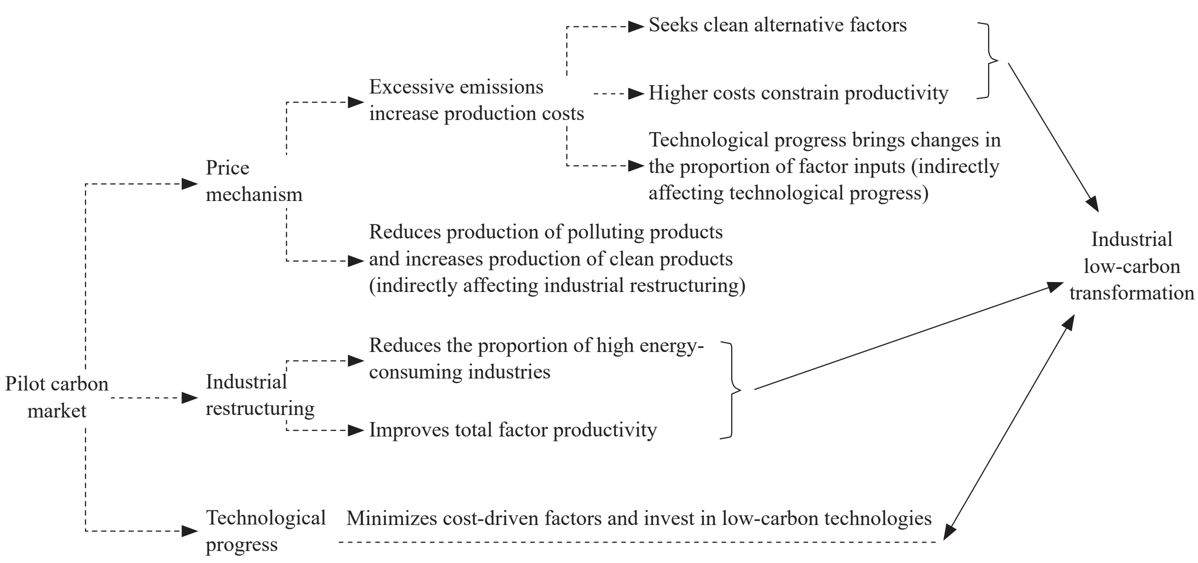

Figure 1: How Pilot Carbon Markets Drive Low-Carbon Industrial Transformation

Based on the theoretical model above, and drawing from equations (14) and (22), the following hypothesis is proposed:

Hypothesis 1: The pilot carbon market is conducive to promoting the process of industrial low-carbon transition.

Existing research indicates that cost constraints serve as an intrinsic incentive for firms to pursue transformation and innovation (Zhao & Li, 2023). Since carbon pricing affects the production costs of industrial goods, firms are compelled either to adopt cleaner alternative inputs to reduce costs or to leverage technological advancements to adjust input combinations, thereby maintaining or enhancing productivity to stay competitive and profitable. The higher the cost of carbon emissions, the greater the pressure on high-emission firms to adopt low-carbon strategies, which in turn increases demand for low-carbon technologies and promotes industrial decarbonization. The carbon trading mechanism plays a direct role in shaping the carbon market's pricing system (Shen & Huang, 2019) and offers firms greater incentives to innovate and transition toward low-carbon operations (Tan & Zhang, 2018). Upgrading industrial structures is a crucial aspect of green industrial transformation (Peng, 2016). Structural improvements support the development of the clean energy sector, foster an enabling environment for innovative, adaptive, and resilient enterprises, and stimulate both upstream and downstream industries to produce or adopt cleaner products. This facilitates the formation of low-carbon industrial supply chains and promotes comprehensive industrial upgrading and decarbonization.

Moreover, the positive impact of technological progress on output growth has been widely recognized in the literature (Bai et al., 2016, 2017). In particular, the development of low-carbon technologies provides essential support for cleaner production processes, equipment upgrades, and the R&D of new products, all of which contribute to pollution reduction and low-carbon industrial transformation (Li et al., 2013). Technological advancements in one sector can not only aid internal emission reductions or productivity gains but also generate spatial spillover effects (Jia et al., 2023). Through pilot carbon markets, such innovations can diffuse across the broader industrial landscape for shared learning. Additionally, competition among peers motivates firms to increase R&D investment in pursuit of higher innovation output, enabling them to attain technological leadership and sustain their competitive advantage.

Based on this theoretical foundation, we propose the following hypothesis:

Hypothesis 2: The pilot carbon market promotes low-carbon transformation through three channels: (1) tightening cost constraints, (2) accelerating industrial restructuring, and (3) spurring technological innovation.

4. Empirical Research Design

4.1 Identification Strategy

Given the staggered implementation of the pilot carbon market across different provinces, this study adopts a multi-period DID approach to accurately identify the policy's effects over time. This method allows for the assessment of both emission reduction and economic efficiency impacts of the carbon market as an environmental regulatory instrument. Specifically, it evaluates the effectiveness of China's industrial low-carbon transition under the carbon trading mechanism, from the dual perspectives of emission control and productivity enhancement. The multi-period DID model is specified as follows:

$$Y_{it}=\beta_0+\beta_1 DID_{it}+\beta_2 Control_{it}+\mu_i+\gamma_t+\varepsilon_{it} \tag{23}$$

In this equation, i denotes the province and t denotes the year. The dependent variable Y includes carbon emission intensity and low-carbon total factor productivity. The core explanatory variable DID is defined as $DID_{it}=treat_i \times post_t$, where $treat_i$ indicates whether a region is part of the carbon market pilot, and $post_t$ reflects whether the pilot program has been implemented in that year. $Control$ represents a set of control variables that account for local characteristics potentially affecting the industrial low-carbon transition. μ_i and γ_t denote province and year fixed effects, respectively, while ε_{it} is the random error term.

4.2 Variable Description

4.2.1 Dependent variable

The dependent variable in this study is industrial low-carbon transition, which reflects not only reductions in carbon emissions but also fundamental changes in the mode of industrial development. Drawing on the definition proposed by Zhou et al. (2022), industrial low-carbon transition refers to the transformation of China's industrial development model through energy conservation, emission reduction, structural upgrading, and technological advancement, aiming to achieve the dual objectives of output growth and emission reduction. This study adopts this definition and measurement approach to assess industrial low-carbon transition through two indicators: carbon emission intensity and low-carbon total factor productivity. It measures emission reduction using the logarithm of provincial industrial carbon emission intensity (*lnco2ei*) as the dependent variable, with data sourced from the China Emission Accounts and Datasets (CEADs). For productivity gains, it uses low-carbon total factor productivity (TFP) as the dependent variable, calculated via the super-efficiency slack-based measure (SBM) model.

Following the approach of Li et al. (2013) and Zhou et al. (2022), this study employs a super-efficiency SBM model incorporating undesirable outputs to reflect environmental impacts within the total factor productivity framework. This model includes input variables, desirable outputs, and undesirable outputs. Input variables consist of capital, labor, and energy. Specifically, capital is measured by the annual average balance of net fixed assets of industrial enterprises, labor is measured by the annual average number of industrial employees, and energy input is measured by total industrial energy consumption. These data are sourced from the *China Industrial Economy Statistical Yearbook*. For missing data in 2017 and 2018, linear interpolation is used to fill in the gaps. Industrial added value serves as the desirable output, while carbon dioxide emissions are treated as the undesirable output.

4.2.2 Core explanatory variable

The core explanatory variable is the DID term, defined as $treat_i \times post_t$. This variable identifies treatment and control groups based on whether the region is subject to the pilot carbon market policy. The treatment group includes seven pilot provinces and cities: Beijing, Shanghai, Tianjin, Guangdong, Hubei, Chongqing, and Fujian. All other non-pilot regions serve as the control group. The $treat_i \times post_t$ variable equals 1 ($treat_i \times post_t = 1$) if province *i* is Beijing, Shanghai, Tianjin, or Guangdong and year *t* is 2013 or later; or if province *i* is Hubei or Chongqing and year *t* is 2014 or later; or if province *i* is Fujian and year *t* is 2016 or later. In all other cases, $treat_i \times post_t$ is set to 0 ($treat_i \times post_t = 0$).

4.2.3 Control variables and other variables

In addition to the core explanatory variable—the pilot carbon market policy—this study includes a range of control variables that may influence the regional industrial low-carbon transition, based on established literature. The level of regional economic development (*PGDP*) is measured by the logarithm of per capita regional GDP, adjusted to 2006 constant prices using the GDP deflator. Economic agglomeration (*lnpop*) is proxied by the logarithm of population density, while regional research and development capacity (*lntmt*) is captured by the logarithm of the technology market transaction volume. Openness to foreign investment (*FDI*) is measured as the share of total foreign investment in regional GDP. Government expenditure (*GOV*) is represented by the ratio of general public budget expenditure to regional GDP. The industrial structure (*INS*) is defined as the proportion of industrial added value in regional GDP. The number of industrial enterprises (*lnNfirm*) is measured by the logarithm of the number of above-scale industrial enterprises in each province. Energy prices (*EP*) are measured using the fuel price index extracted from each region's commodity retail price index.

In the mechanism analysis, the study further incorporates specific variables to measure relevant channels. The carbon price (*lnprice*) is represented by the logarithm of the annual average of daily closing prices. Industrial structure upgrading (*highper*) is measured by the proportion of output from high-energy-consuming industries[1]. This variable serves as a negative indicator, where a higher value implies lower structural upgrading. Technological progress (*lnpatent*) is measured by the logarithm of the number of invention patents granted to above-scale industrial enterprises.

4.3 Data Sources and Descriptions

4.3.1 Data sources

This study is based on panel data covering 30 provinces in China from 2006 to 2021, excluding the Xizang Autonomous Region. Except for carbon dioxide emissions and energy consumption, all regional-level data are obtained from the *China Statistical Yearbook (2007-2022)* and the *China Environmental Statistical Yearbook*. For the missing 2018 data on provincial industrial added value, the national ratio of industrial added value to secondary industry added value is used as a uniform coefficient to estimate the provincial values. For the heterogeneity analysis, industry-level data on carbon emissions and energy consumption are sourced from the China Emission Accounts & Datasets (CEADs), based on the CEADs industry classification. The study retains only industrial sectors and consolidates them into 36 aggregated categories. Because energy consumption comprises multiple sources—including coal, petroleum, natural gas, electricity, heat, and others—with different measurement units that cannot be directly aggregated, all energy types are converted into standard coal equivalent (10,000 tons) using the reference coefficients provided in the *China Energy Statistical Yearbook*. This conversion ensures the comparability and consistency of energy consumption data across sectors and provinces.

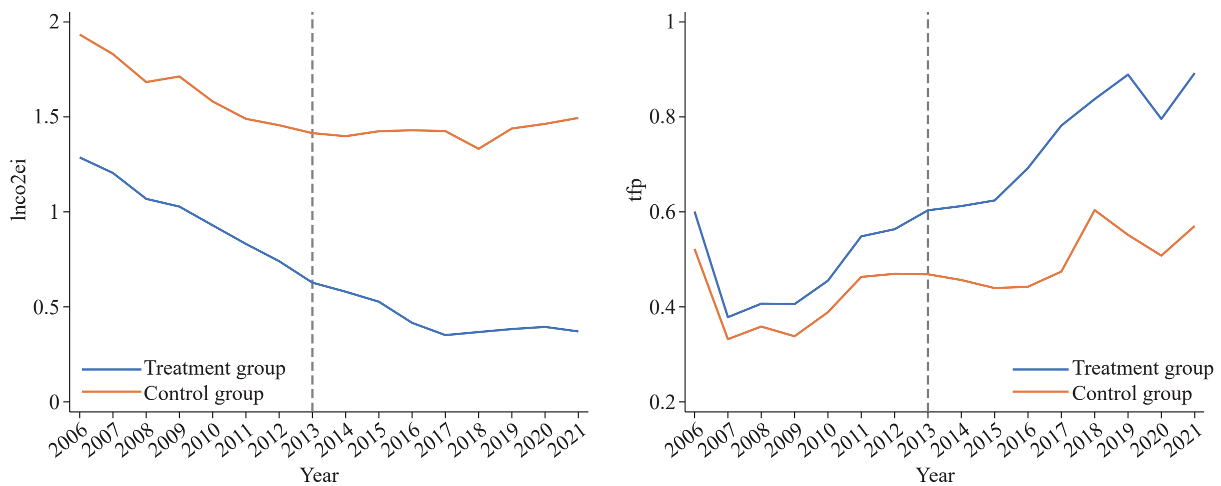

Figure 2: Annual Averages of Carbon Emission Intensity and Low-Carbon Total Factor Productivity for Treatment and Control Groups

[1] Following Deng (2019), who identifies six major energy-intensive sectors: chemical raw materials and chemical products manufacturing, non-metallic mineral products, ferrous metal smelting and rolling, non-ferrous metal smelting and rolling, petroleum processing and coking, and electric and thermal power production and supply.

4.3.2 Descriptive characteristics of key variables

Figure 2 depicts the annual mean trends in carbon emission intensity and low-carbon total factor productivity for the treatment and control groups. The treatment group consistently shows lower carbon emission intensity and higher output growth than the control group. Both groups shared similar trends before the pilot carbon market policy, confirming the parallel trend assumption. Post-policy, the treatment group exhibits a stronger policy effect, highlighting the pilot carbon market's role as an effective quasi-natural experiment for studying industrial low-carbon transition across Chinese provinces. These data patterns provide a robust foundation for applying the DID approach.

5. Analysis of the Pilot Carbon Market's Role in Promoting Industrial Low-Carbon Transition

5.1 Baseline Regression

This study argues that the pilot carbon market affects industrial low-carbon transition through two main channels: reducing emissions and enhancing efficiency. Accordingly, the DID method is employed to estimate the treatment effects of the carbon market on industrial carbon emission intensity and low-carbon total factor productivity. Table 1 presents the baseline regression results derived from estimating equation (1) using provincial panel data. In columns (1) and (3), regressions are performed without the inclusion of control variables, while all regressions incorporate both year and province fixed effects. Standard errors are clustered at the provincial level to account for within-region correlation. In terms of emission reduction, the coefficient of the core explanatory variable DID in column (1) is significantly negative at the 1% level, indicating that the pilot carbon market effectively suppresses industrial carbon emission intensity. To mitigate concerns over omitted variable bias, column (2) introduces control variables related to regional characteristics. Although the magnitude of the coefficient slightly decreases, it remains statistically significant at the 1% level. Regarding efficiency enhancement, the DID coefficients in columns (3) and (4) are both significantly positive at the 1% level, suggesting that the implementation of the carbon market pilot has spurred industrial output growth and improved low-carbon total factor productivity. Quantitatively, the results imply that the pilot carbon market reduces carbon emission intensity by an average of approximately 25.3% and increases low-carbon total factor productivity by about 9.7%. These findings provide preliminary empirical support for the view that the pilot carbon market contributes to industrial low-carbon transition, thereby validating Hypothesis 1.

Table 1: Baseline Regression Analysis

Variable	(1)	(2)	(3)	(4)
	lnco2ei	*lnco2ei*	*tfp*	*tfp*
DID	-0.317***	-0.253***	0.176***	0.097***
	(0.111)	(0.074)	(0.045)	(0.031)
_cons	1.783***	-0.827	0.540***	1.090
	(0.046)	(3.295)	(0.036)	(1.316)
Control variables	NO	YES	NO	YES
Year fixed effects	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
N	480	480	480	480
adj. R^2	0.492	0.802	0.465	0.727

Note: Robust standard errors clustered at the provincial level are reported in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01. The same notation applies to all subsequent tables.

5.2 Dynamic Effect Test

This study adopts the methodological framework of Beck et al. (2010) and Wu et al. (2021) to assess the dynamic treatment effects of the pilot carbon market policy and to further validate the parallel trends assumption underlying the DID approach. We examine a 13-year period centered on the policy implementation year, covering six years before and six years after the official launch of the carbon market pilot. The year that is seven years prior to implementation is excluded from the main analysis[2] and instead serves as the baseline year for comparison[3]. Following the event study approach, we construct a specific model based on this baseline, as detailed below.

$$Y_{it}=\alpha_0+\beta_1 D_{it}^{-6}+\beta_2 D_{it}^{-5}+\cdots+\beta_{13} D_{it}^{6}+\alpha_1 Control_{it}+\mu_i+\gamma_t+\varepsilon_{it} \tag{24}$$

The interaction term D_{it}^{j} represents the product of the pilot year dummy variable and the corresponding policy dummy variable. Its value is defined as follows: it equals 1 if province i is in the j^{th} year before or after the implementation of its carbon market pilot policy in year t; otherwise, it equals 0. All other variables retain the same meanings as in the baseline model. The coefficient β measures the difference in industrial low-carbon transition between provinces that implemented the carbon market pilot policy and those that did not. If β is statistically insignificant for $j<0$, it suggests no significant pre-treatment difference in industrial low-carbon transition between pilot and non-pilot provinces, thereby supporting the parallel trend assumption. For $j\geq 0$, the coefficient β captures the annual treatment effect of the pilot policy; if β is statistically significant, it indicates that the implementation of the carbon market pilot had a substantive impact on industrial low-carbon transition in that year.

It is important to note that an unbiased estimation of the policy's treatment effect depends on both the parallel trend assumption and the absence of spillover effects—that is, the treatment should not affect the control group. In this study, non-pilot provinces are used as the control group for evaluating the impact of carbon market pilots. If any provinces in the control group are influenced by spillover effects from the policy, it could distort the estimation of the true treatment effect. A more detailed discussion of spillover effects is provided later in the text.

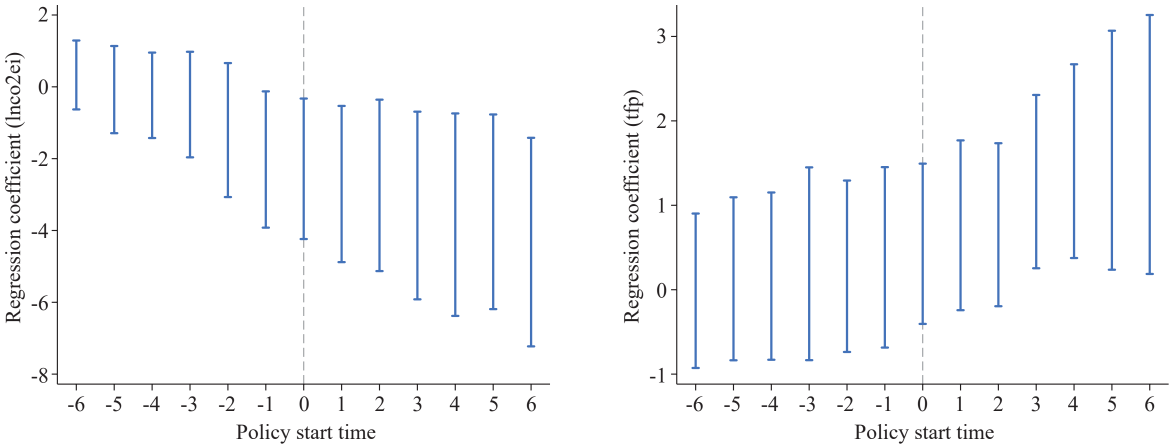

Figure 3: Dynamic Effects of the Pilot Carbon Market

[2] This paper takes 2013, the official launch year of the carbon market pilot, as the policy shock time point. However, due to the different implementation times of the carbon market pilot policies, a small number of samples have time points of -8, -9, and -10 relative to the policy shock, so these small number of samples are merged into the -7 time point.

[3] Regarding the setting of the base period, most existing literatures use the initial year of sample observation, the year of policy implementation, or the year before policy implementation as the comparison benchmark.

Figure 3 illustrates the dynamic effects of the pilot carbon market on industrial low-carbon transition. The dynamic effect regression results in Figure 3 (left) show that coefficient β is close to zero and insignificant for the interval $-6 \leq j \leq -2$. This indicates no significant difference in carbon emission intensity between the treatment and control groups before the pilot carbon market policy, thus satisfying the parallel trend assumption. The pilot carbon market's treatment effect on emission reduction begins to emerge when β is at j = -1, with the carbon reduction effect reaching its peak in the fourth year after implementation. In fact, related studies (Hu et al., 2019; Wu et al., 2021) have also found that pilot carbon market regions exhibit an "anticipatory policy effect". This means that after China proposed and began preparations for carbon market construction by the end of 2011, closely related high-carbon emission sectors proactively reduced their carbon emissions.

As shown in Figure 3 (right), coefficient β is almost close to zero and not significantly different from zero when $j \leq 0$, indicating no significant difference in low-carbon total factor productivity between the treatment and control groups before the pilot carbon market policy. This again satisfies the parallel trend assumption. The effect becomes significant when β is at j = 3, suggesting that the pilot carbon market's treatment effect begins to show an efficiency-enhancing trend. Specifically, low-carbon total factor productivity in pilot regions steadily improves in the third year after policy implementation, significantly increases further in the fourth year, and maintains a high productivity level thereafter. This result confirms a lagged effect of the pilot carbon market on productivity enhancement. It implies that in the short term, industrial sectors may achieve emission reduction targets at the cost of output growth. However, in the long run, under the dual pressures of economic growth and emission reduction, industries achieve a new growth model of high output and low emissions through technological improvement, industrial restructuring, and other channels.

5.3 Placebo Test and Time Heterogeneity

5.3.1 Placebo test

Following Bai et al. (2022), this study conducted a placebo test by randomly assigning policy implementation years and treatment groups. Industrial low-carbon transition may be influenced by concurrent policies or unobserved factors, potentially biasing estimated effects. To address this, pseudo-carbon market pilot policies were constructed. If placebo coefficients remained significant, it would suggest that differences between treatment and control groups stem from confounding factors. If insignificant, it would confirm that observed effects are primarily due to the carbon market pilot, supporting result robustness. The method involved 500 random simulations across 30 provinces, with 7 provinces randomly selected as the treatment group and implementation years randomly assigned in each simulation, generating 500 sets of placebo dummy variables (*didrandom*). For emission reduction, placebo coefficients clustered around zero, with most p-values exceeding 0.1, while the actual policy coefficient was -0.253 and significant. For productivity enhancement, placebo coefficients were mostly negative, with p-values above 0.1, compared to the actual policy coefficient of 0.097, which was significant. These differences indicate that policy effects are unlikely driven by unobserved confounders, confirming the robustness of baseline results.

5.3.2 Time heterogeneity

The staggered implementation of the carbon market pilot may introduce time-varying heterogeneity, leading to inconsistent policy effects and biased estimations. According to Goodman-Bacon (2021), the two-way fixed effects (TWFE) estimator is a weighted average of all possible two-by-two DID comparisons. If regions that adopted the policy earlier are mistakenly used as controls for those treated later, the estimated treatment effect may become exaggerated or even reversed as the sample period extends (Baker et al., 2022). To address this issue, we follow the decomposition approach proposed by

Goodman-Bacon (2021) to break down the overall DID coefficient from the TWFE model. This allows us to identify the contributions of different group comparisons and isolate the "pure" treatment effect of the carbon market pilot on China's industrial low-carbon transition.

Table 2 presents the Goodman-Bacon decomposition results, comprising: (1) DID estimates comparing earlier-treated regions to later-treated regions (Earlier treated vs. Later control), (2) DID estimates comparing later-treated regions to earlier-treated regions (Later treated vs. Earlier control), and (3) DID estimates comparing all treated regions to never-treated regions (Treated vs. Never treated), which represent the primary effect of interest. The potentially biased DID component—comparing later-treated regions to earlier-treated regions (Later treated vs. Earlier control)—carries a low weight of approximately 3.2%, resulting in minimal bias in the overall treatment effect. Conversely, the primary comparison—treated versus never-treated regions—accounts for about 96.8% of the weight, demonstrating that valid comparisons predominantly drive the findings. These results confirm that estimation bias from treatment timing heterogeneity remains negligible, strongly supporting the credibility and robustness of the study's conclusions.

Table 2: Weights and Coefficients from Goodman-Bacon (2021) Decomposition

Component	Panel A: *lnco2ei*	
	Weight	Coefficient
Earlier treated vs. Later control	0.016	0.042
Later treated vs. Earlier control	0.015	-0.065
Treated vs. Never treated	0.968	-0.327
DID	-0.317	
Component	Panel B: *tfp*	
	Weight	Coefficient
Earlier treated vs. Later control	0.016	-0.003
Later treated vs. Earlier control	0.015	0.025
Treated vs. Never treated	0.968	0.182
DID	0.176	

Note: The Goodman-Bacon (2021) decomposition illustrates the weights and components that constitute the DID coefficient, where "Treated" refers to provinces implementing the carbon market pilot. Panel A presents the decomposition results for industrial carbon emission intensity, while Panel B covers low-carbon total factor productivity. All models are estimated following Equation (23). For ease of comparison, each component's weight and point estimate are reported alongside the overall model estimate. None of the individual components are statistically significant at the 95% confidence level.

5.4 Endogeneity Handling

To address potential endogeneity concerns—such as reverse causality between the carbon market pilot and industrial low-carbon transition, or omitted variable bias—this study adopts two strategies: the instrumental variable (IV) approach and lagged control variables. First, we use the regional air circulation coefficient as an instrument for the carbon market pilot. This variable satisfies the relevance condition, as regions with poor air circulation typically face more severe carbon emissions, making them more likely to implement stringent environmental regulations such as carbon trading pilots. At the same time, as a natural and objective environmental characteristic, the air circulation coefficient has limited direct influence on industrial low-carbon transition, satisfying the exogeneity requirement. The first-stage regression confirms the instrument's relevance and passes the tests for under-identification and exogeneity. In the second-stage regression, the carbon market pilot remains positively associated with industrial low-carbon transition. The estimated DID coefficient is larger than in the baseline regression, suggesting that addressing endogeneity reveals an even stronger policy effect. Second, acknowledging that finding a perfect instrument is challenging and instrument selection is not always unique, we also follow the approach of Xu & Sun (2023) by lagging all control variables by one period. This further mitigates potential endogeneity concerns, and the results remain robust.

5.5 Additional Robustness Checks

To ensure that the baseline findings are not driven by confounding factors, we conduct a series of robustness checks. These include reconstructing the industrial low-carbon transition index, incorporating additional control variables, accounting for other policies in effect during the sample period, and applying the synthetic control method.

5.5.1 Comprehensive evaluation using the entropy method

This study incorporates both emission reduction and efficiency improvement into the evaluation framework, constructing a multidimensional indicator system across four dimensions: energy conservation and emission reduction, structural upgrading, technological progress, and factor intensiveness. The entropy method is employed to comprehensively assess industrial low-carbon transition. Regression results indicate that the pilot policy continues to significantly promote industrial low-carbon transition.

5.5.2 Incorporating additional control variables

While the baseline regression controls for province fixed effects and several regional-level variables, there may still be omitted variables that influence industrial low-carbon transition in the pilot provinces, potentially biasing the estimates. To address this issue, we incorporate additional observable control variables, including structural optimization, urbanization, and technological progress. Results show that although the coefficient of the core explanatory variable slightly decreases, it remains statistically significant at the 1% level, confirming the robustness of the estimated policy effect.

5.5.3 Controlling for other policy interference

To avoid estimation bias caused by overlapping policies during the sample period, this study accounts for three major national initiatives: the Low-Carbon City Pilot launched in 2010 (Wang & Ge, 2022), the *Air Pollution Prevention and Control Action Plan* initiated in 2013 (Yang et al., 2020), and the "Made in China 2025" demonstration cities established between 2016 and 2017 (Wang et al., 2023). We introduce three corresponding policy dummy variables—policy10, policy13, and policy17—which equal 1 if the respective policy was implemented in a province-year, and 0 otherwise. Regression results show that, after controlling for these policies, the coefficient on the DID policy variable remains significant at the 1% level, and its magnitude is nearly unchanged from the baseline. This indicates that the baseline results are robust to potential interference from other concurrent policies.

5.5.4 Synthetic control method

China's carbon market pilots were not randomly assigned; instead, provinces or municipalities with more developed financial systems and higher levels of economic development were deliberately selected to take the lead in pilot implementation. These regions were also more advanced in institutional mechanisms and energy-saving policies, raising concerns about selection bias. While prior studies have often used propensity score matching (PSM) to mitigate such bias by pairing each treated province with a comparable control for DID estimation (Cheng & Yang, 2023; Jia et al., 2023), PSM is more appropriate for large micro-level datasets. In contrast, this study uses provincial-level data with a limited sample size, where the common support assumption may not hold, leading to poor matches and biased results. To address this, we apply the synthetic control method, which is more suitable for small samples.

This approach constructs a counterfactual control group that closely resembles the first batch of carbon market pilot provinces, allowing for a re-evaluation of the policy's impact. The estimation results show no significant differences between the synthetic control and treatment groups prior to the policy announcement. However, following the official launch of the carbon market, treated regions exhibit clear divergence from their synthetic counterparts. Overall, these results are consistent with those from the baseline regression, reinforcing the validity of the main findings.

6. Mechanism Testing: How the Pilot Carbon Market Facilitates Industrial Low-Carbon Transition

Building on the preceding analysis that confirmed the emission reduction and efficiency-enhancing effects of the pilot carbon market, this section employs econometric models to test three proposed transmission mechanisms—cost constraints, structural upgrading, and technological innovation (collectively referred to as "Z"). These mechanisms are theoretically conducive to promoting industrial low-carbon transformation. However, whether the pilot carbon market effectively activates these channels remains an open question. To address this, the study constructs a mechanism verification framework to empirically assess whether the carbon market can promote industrial low-carbon transition via these intermediate pathways:

$$Z_{it}=\beta_0+\beta_1 DID_{it}+\beta_2 Control_{it}+\mu_i+\gamma_t+\varepsilon_{it} \tag{25}$$

6.1 Cost Constraint

Excessive CO_2 emissions have caused severe global climate impacts, making carbon emission control an urgent imperative. Carbon markets serve as a market-based tool to regulate total emissions and allocate carbon allowances. Heavily polluting enterprises, which often cannot reduce emissions substantially in the short term, typically face allowance shortages. In contrast, cleaner industries or energy-efficient firms may hold surplus allowances. Trading in the carbon market enables optimal reallocation of these resources.The regulatory role of the carbon market hinges on carbon pricing. As carbon prices rise, firms face increased production costs. This economic pressure compels high-emission enterprises to either adopt cleaner inputs or invest in technological upgrades to optimize input structures and reduce emissions. In the long term, firms that improve their low-carbon technologies can lower their abatement costs. This not only reduces emissions but also allows them to benefit from selling excess allowances, thus reinforcing a virtuous cycle: cost minimization → investment in low-carbon technology → emission reduction. These dynamics contribute to improving overall industrial output performance. Moreover, under mounting environmental regulatory pressure, highly polluting enterprises that are unable to bear the cost of emission reductions are likely to be phased out. The surviving firms are, on average, better equipped with cleaner technologies and possess stronger innovation capabilities.

As discussed earlier, the pilot carbon market may directly affect carbon emission intensity and indirectly influence productivity through the cost constraint mechanism. To empirically validate this pathway, this study examines the impact of the pilot carbon market on carbon prices. Column (1) of Table 3 reports a significantly positive regression coefficient when the logarithm of carbon price (*lnprice*) is used as the dependent variable. This result indicates that the pilot carbon market has effectively driven up carbon prices. In turn, higher carbon prices raise industrial firms' production costs, which, via the cost constraint channel, reduces carbon emission intensity and enhances low-carbon total factor productivity, thereby promoting the industrial low-carbon transition.

6.2 Industrial Structure Upgrading

Driven by environmental pressures and market competition, outdated production capacities are increasingly phased out, while new drivers of growth are activated. This transition promotes the transformation and low-carbon upgrading of polluting and energy-intensive industries, reducing their share within the industrial sector. At the same time, it increases the proportion of low-carbon industries and those better positioned to adapt to structural change, thereby optimizing the overall industrial layout. In the carbon trading system, polluting and energy-intensive industries face a clear cost disadvantage. The previously prevalent model of achieving high output at the expense of environmental damage is no longer viable. Intensified market competition forces these industries to either relocate or restructure. Simultaneously, structural improvements support the development of clean energy sectors and foster an enabling environment for innovative and adaptive firms. These changes collectively drive industrial structure upgrading and support the broader shift toward low-carbon development. Empirical results in Table 3, Column (2), use the share of polluting and energy-intensive industries (*highper*) as the dependent variable. Findings show that, following the implementation of the carbon market pilot, this share significantly declined, with an average reduction of 14.3%. This suggests that, under strong environmental constraints, China's industrial sector has actively promoted clean industries and advanced structural optimization, thereby contributing to both emissions reduction and productivity gains—and ultimately, to industrial low-carbon transition.

Table 3: Mechanism Test Analysis

Variable	(1)	(2)	(3)
	lnprice	*highper*	*lnpatent*
DID	3.063***	-0.143***	-0.122
	(0.143)	(0.048)	(0.084)
_cons	-0.372	-5.687*	2.556
	(1.770)	(2.945)	(3.058)
Control variable	YES	YES	YES
Year fixed effects	YES	YES	YES
Province fixed effects	YES	YES	YES
N	480	330	480
adj. R^2	0.926	0.617	0.942

6.3 Technological Progress

As the core component of carbon market development, the carbon emissions trading system serves as a market-based regulatory instrument that plays a vital role in advancing the low-carbon and sustainable transformation of China's industrial sector. Existing literature—much of it grounded in the Porter Hypothesis—remains divided on whether environmental regulations effectively stimulate technological innovation to achieve sustainable economic growth. The impact of environmental regulation on innovation typically reflects two opposing forces: the innovation compensation effect, where innovation offsets compliance costs, and the compliance cost effect, where such costs hinder innovation. The balance between these effects varies across empirical studies, but there is broad agreement that firms must invest considerable technological effort to reap the benefits of innovation compensation. By turning carbon into a tradable commodity, the carbon market presents firms with two potential responses to excess emissions: purchasing additional allowances or reducing emissions through technological innovation. The decision depends on cost-benefit trade-offs—firms are more likely to pursue innovation when carbon prices are high or volatile, as this reduces long-term abatement costs.

Due to data limitations, this study uses the number of invention patents granted to above-scale industrial enterprises as a proxy for technological progress, measured by the logarithm of invention patents (*lnpatent*), which reflects R&D output. According to the results in Table 3, Column (3), the pilot carbon market has not produced a statistically significant increase in the number of invention patents.

This finding suggests that, although the rising cost of carbon emissions may provide incentives for innovation, actual technological progress is constrained by long R&D cycles, technical barriers, and inherent uncertainties. These factors likely explain the lack of a significant effect in the short term. As a result, the pilot carbon market has not yet substantively advanced industrial low-carbon transition via the technological progress channel.

Hence, Hypothesis 2 is fully supported.

7. Spillover Effects and Heterogeneity Analysis of the Pilot Carbon Market Policy on Low-Carbon Transition

As previously noted, unbiased estimation of policy effects using the DID approach relies on the parallel trends assumption and the absence of spillover effects. This section tests for potential spillovers from the pilot carbon market policy and further explores whether the low-carbon transition varies across regions and industries under the carbon market and emission reduction goals.

7.1 Spillover Effects

Prior studies have found strong spatial correlations in pollution emissions across Chinese regions, suggesting that pilot carbon market policies may generate spatial spillover effects. For example, Dong & Wang (2021) identified a demonstration effect, whereby the implementation of local carbon trading policies led to emission reductions in neighboring regions.To provide background, this study calculated pre-policy industrial carbon emission intensity across provinces. Ningxia had the highest intensity—averaging 20.61 tons of CO_2 per 10,000 yuan of industrial added value—followed by Inner Mongolia, Guizhou, Shanxi, and Gansu, all around 10 tons per 10,000 yuan. Following Clarke and Mühlrad (2021), two approaches were used to test for spillover effects: first, an interaction term (*highEI*) was added between post-policy implementation and provinces with high emission intensity, excluding the seven pilot provinces. Second, eight provinces neighboring the pilot regions (Hebei, Zhejiang, Guangxi, Jiangxi, Anhui, Hunan, Guizhou, and Sichuan) were selected[4]. An interaction term (*Spill*) between post-policy implementation and these provinces was included in the baseline regression. The results, reported in Table 4, show no significant evidence that the pilot policy influenced emissions or efficiency in non-pilot provinces. This confirms that the baseline DID estimates are both credible and unbiased.

Table 4: Analysis of Spillover Effects

Variable	Provinces with high industrial carbon emission intensity		Neighboring provinces	
	lnco2ei	*tfp*	*lnco2ei*	*tfp*
DID			-0.287*** (0.081)	0.103*** (0.033)
highEI	0.072 (0.068)	-0.011 (0.024)		
Spill			-0.110 (0.082)	0.019 (0.031)

[4] Eight provinces neighboring the pilot regions (Hebei, Zhejiang, Guangxi, Jiangxi, Anhui, Hunan, Guizhou, and Sichuan) were selected.

Table 4 Continued

Variable	Provinces with high industrial carbon emission intensity		Neighboring provinces	
	lnco2ei	*tfp*	*lnco2ei*	*tfp*
_cons	-3.881 (4.435)	1.763 (1.788)	-1.114 (3.164)	1.139 (1.293)
Control variables	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES
N	368	368	480	480
adj. R^2	0.765	0.633	0.807	0.727

7.2 Heterogeneity Analysis

7.2.1 Regional heterogeneity

While the preceding analysis has evaluated the average effect of the pilot carbon market policy on China's industrial low-carbon transition, regional disparities in economic development, technological capacity, and investment environments may result in heterogeneous impacts. In general, economically developed regions tend to have more advanced industrial structures, enabling them to more effectively reduce carbon emission intensity and capitalize on the benefits of carbon market mechanisms. These regions also have the resources—both human and financial—to support carbon market implementation and to drive the growth of tertiary and low-carbon industries. In contrast, less developed regions may lack the technical expertise and financial capacity to improve productivity while also reducing emissions. Technological capability plays a central role in determining regional productivity outcomes. Regions with stronger innovation capacity can reallocate inputs more efficiently through technological progress—for example, by increasing the use of clean energy to lower emissions or by reducing total input use to enhance productivity. By contrast, regions with weaker R&D systems are more likely to rely on outdated production technologies due to innovation barriers, leading to divergent effects in emission reduction and efficiency gains. In addition, the carbon market policy may channel both domestic and foreign investment into low-carbon industries. Regions with favorable investment environments are better positioned to attract these investments, enhancing their industrial competitiveness and driving productivity improvements through innovation-led growth.

To explore the heterogeneous effects of the pilot carbon market policy on regional industrial low-carbon transition, this study incorporates interaction terms between the DID policy indicator and key regional characteristics into the baseline regression model. A significant interaction term coefficient confirms the presence of heterogeneity. Table 5 reports the results of subgroup regressions. Group 1 includes the interaction between the pilot carbon market policy and per capita GDP. For carbon emission intensity (***lnco2ei***) as the dependent variable, the interaction term is significantly negative, indicating stronger emission reductions in more developed areas. For low-carbon total factor productivity (***TFP***) as the dependent variable, the interaction term is significantly positive, showing greater productivity gains in more developed areas. These findings suggest that carbon markets drive more effective low-carbon industrial transformation in more developed areas.

Group 2 incorporates an interaction term between the DID policy indicator and technology market turnover, a proxy for regional R&D capacity, into the regression. The results show that the interaction term's coefficients are statistically significant for both *lnco2ei* and *TFP*. This indicates that carbon markets in regions with higher R&D capacity drive greater emission reductions and productivity gains. These findings align with the theoretical mechanism outlined earlier, confirming that carbon trading promotes low-carbon industrial transformation through technological progress. Group 3 incorporates the interaction between the DID policy indicator and regional openness, measured by foreign direct investment (*FDI*), into the regression. When the dependent variable is carbon emission intensity (***lnco2ei***), the interaction term is not statistically significant, but the DID coefficient is significantly negative, indicating consistent emission reductions across regions regardless of investment environment. When the dependent variable is low-carbon total factor productivity (***TFP***), the interaction term is significantly positive, revealing heterogeneous productivity effects. Areas with stronger investment environments attract greater investment in low-carbon technology R&D under carbon market policies. This increased investment, combined with enhanced market competition from greater firm participation, boosts R&D output and improves factor productivity.

Table 5: Regional Heterogeneity Analysis

Variable	Group 1		Group 2		Group 3	
	lnco2ei	*tfp*	*lnco2ei*	*tfp*	*lnco2ei*	*tfp*
DID	0.236 (0.201)	-0.185* (0.092)	0.210 (0.189)	-0.117* (0.063)	-0.184*** (0.062)	0.041 (0.024)
DID×lnpgdp	-0.285* (0.139)	0.163** (0.060)				
DID×lntmt			-0.074** (0.030)	0.034*** (0.012)		
DID×FDI					-0.095 (0.067)	0.076** (0.033)
_cons	-0.804 (3.267)	1.076 (1.268)	-1.119 (3.346)	1.224 (1.300)	-1.217 (3.419)	1.405 (1.313)
Control variable	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES	YES	YES
N	480	480	480	480	480	480
adj. R^2	0.807	0.734	0.809	0.733	0.803	0.731

7.2.2 Industry heterogeneity

Under the dual context of rising environmental pressure and the establishment of the carbon market system, industries exhibit distinct responses in behavior and decision-making. High-pollution industries—which emit large volumes of greenhouse gases such as CO_2 and SO_2—pose major challenges to sustainable development. These sectors often face carbon allowance shortfalls and must purchase additional quotas through the carbon market to maintain output levels. As a result, they are more directly affected by carbon pricing policies, which may also stimulate technological innovation as a response to regulatory and cost pressures. In contrast, mid- and low-pollution industries are subject to less direct environmental pressure, as their production processes are less dependent on carbon emissions. Consequently, their motivation for adopting low-carbon technologies or transforming production practices may stem more from reputational considerations than regulatory necessity. These differences suggest that the pilot carbon market policy may exert heterogeneous effects across industries. To test this, the industrial sector is classified into high-pollution and mid-low-pollution categories, and the Regression results are reported in Table 6[5].

[5] Following the approach of Pan (2019), high-pollution industries include chemical manufacturing, chemical fibers, nonferrous and ferrous metal smelting and mining, coal mining, power and heat supply, petroleum extraction and processing, leather and footwear, paper manufacturing, textiles, non-metallic mineral products, and rubber and plastics. All other industrial sectors are grouped as mid-low pollution industries.

Table 6 reports the regression results based on the adjusted full sample[6], as well as separate regressions for high-pollution and mid-to-low-pollution industries. All regressions control for year, province, and industry fixed effects, with control variables retained at the provincial level, and standard errors clustered by province. The results indicate that the baseline effects of the pilot carbon market on emission reduction and efficiency improvement in China's industrial sector are robust. Subsample analysis shows that the pilot carbon market policy significantly reduces carbon emission intensity in high-pollution industries, but exhibits no statistically significant heterogeneous effects for mid-to-low-pollution industries or for low-carbon total factor productivity across industry types. These findings suggest that the emission reduction effect of the pilot carbon market is primarily concentrated in high-pollution industrial sectors.

Table 6: Industry Heterogeneity Results

Variable	Total samples		High-pollution sectors		Mid-and low-pollution Sectors	
	lnco2ei	*tfp*	*lnco2ei*	*tfp*	*lnco2ei*	*tfp*
DID	-0.199*	0.053*	-0.213***	0.048	-0.185	0.057
	(0.098)	(0.005)	(0.068)	(0.058)	(0.175)	(0.055)
_cons	-1.866	-2.819	-2.421	-5.597*	2.476	-0.058
	(6.033)	(2.904)	(5.186)	(3.169)	(9.516)	(3.877)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES
Province fixed effects	YES	YES	YES	YES	YES	YES
Industry fixed Effects	YES	YES	YES	YES	YES	YES
N	840	480	420	240	420	240
adj. R^2	0.953	0.696	0.977	0.851	0.889	0.811

8. Research Conclusions and Policy Recommendations

Based on provincial panel data from 2006 to 2021, this study constructs a theoretical mechanism model and employs a multi-period DID approach to comprehensively evaluate the environmental and economic effects of China's pilot carbon market policy. The main conclusions are as follows:

First, the pilot carbon market has significantly reduced carbon emission intensity in China's industrial sector while improving low-carbon total factor productivity. These results remain robust after a series of tests, including the parallel trend test, placebo test, and multiple robustness checks.

Second, the carbon market mainly promotes industrial low-carbon transition by strengthening cost constraints and facilitating industrial structure upgrading. These are the two primary transmission channels. However, the policy has not yet demonstrated a significant effect on technological progress, which is considered a core driver of long-term low-carbon industrial transformation.

Third, the impact of the carbon market exhibits regional heterogeneity. Specifically, regions with higher levels of economic development and R&D capacity show more significant emission reduction and efficiency improvement effects. In contrast, while foreign investment intensity does not result in heterogeneous effects on emission reduction, it does significantly enhance productivity in regions with stronger investment environments.

Under the context of the national "carbon peaking and neutrality" goals and increasing environmental pressures, a well-developed carbon emissions trading market may serve as a new pathway for industrial restructuring and transformation in China. It also constitutes a critical foundation for the establishment

[6] Full-sample data covers the period from 2008 to 2016.

of a unified national carbon market across the entire industrial chain. Based on the above findings, this study offers the following policy recommendations:

(1) Given the carbon market's key role in driving industrial low-carbon transformation, China should actively advance its carbon market development. By analyzing regional differences in industrial growth and carbon emissions, the carbon market should include more pilot provinces or regions and steadily expand its scope. Local governments and carbon trading institutions should organize collaborative exchange activities to discuss and propose practical recommendations for carbon market development. The government should increase financial allowances, recruit skilled professionals to design robust mechanisms, and build a fair and efficient carbon trading system. These steps aim to create clear pathways for achieving regional development and emission reduction goals while delivering effective solutions to environmental challenges.

(2) Crafting sustainable development plans tailored to regional and industrial characteristics—such as industrial features, development stages, economic conditions, and spatial layouts—is essential. These plans should clearly define transformation pathways for traditional industrial regions to align with national goals for industrial restructuring. This approach fosters a virtuous cycle of "industrial transformation — environmental improvement — emergence of new industries — elimination of outdated capacities — further industrial transformation", ultimately driving sustainable development across both industrial and other sectors.

(3) Supporting innovative enterprises through tax incentives, allowances, and similar measures is key to stimulating investment in low-carbon technologies, talent development, and the resolution of R&D challenges. At the same time, improving the investment climate will help attract funding for low-carbon research and development projects. Together, these initiatives will enhance market competitiveness, increase R&D output, and raise production efficiency, achieving a harmonious "win-win" of emission reduction and economic gain.

(4) Empowering local regions to develop diverse carbon trading models allows for approaches that reflect specific emission reduction needs. These models should emphasize the growth of carbon finance products and services, while encouraging greater participation from regulated entities and market players in emissions control and trading. By fully leveraging the synergy between efficient markets and state capacity, we can accelerate the full harmonization of regional carbon markets with the national carbon market framework.

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