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How Does Incentive-Based Environmental Regulation Promote Employment? A Quasi-Natural Experiment Based on Carbon Trading Rights Pilot

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Abstract

Treating the pilot carbon emissions trading policy as a quasi-natural experiment, this study employs a multi-period difference-in-differences model to assess its employment effects using panel data from Shanghai and Shenzhen A-share listed companies between 2007 and 2022. Results indicate that the pilot policy effectively promotes corporate employment, with the most significant positive impacts observed in private enterprises, secondary industry firms, and technology-intensive companies. The pilot policy promotes corporate employment through three intermediary pathways: “scale–output,” “factor substitution and complementarity,” and “innovation compensation.” “Financing constraints” exert a moderating effect on these pathways, weakening the promotional impact. The pilot policy increases corporate demand for highly educated and technical talent, generating labor mobility effects across regions and industries. The study provides actionable insights for employment effects arising from carbon emissions trading market development.

Keywords: environmental regulation; carbon emissions trading; employment; moderated intermediary effects; policy spillovers

1. Introduction

To address the unknown risks posed by accelerating global warming and fulfill the responsibilities of the world’s second-largest economy, General Secretary Xi Jinping announced the “dual carbon” goals—carbon peak and carbon neutrality—at the 75th session of the United Nations General Assembly. The Third Plenary Session of the 20th CPC Central Committee similarly emphasized focusing on building a Beautiful China, accelerating the comprehensive green transformation of economic and social development, establishing a green and low-carbon spatial pattern for high-quality development, reducing carbon emissions and excessive consumption of fossil fuels, promoting the green and low-carbon transformation and upgrading of traditional industries, and steadily advancing the goals of carbon peak and carbon neutrality.

Driven by the dual carbon goals, China has successively introduced a series of carbon reduction measures, strengthening environmental regulation and oversight. Explicit environmental regulations can be categorized into mandatory, incentive-based, and voluntary types [1] (pp. 86–90). Mandatory environmental regulations primarily involve directives



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issued by the central government, such as the “Ten Measures for Air Pollution Prevention and Control,” the “13th Five-Year Plan for Ecological and Environmental Protection,” and the “Clean Energy Indicators,” which explicitly stipulate “hard constraint” emission reduction targets. The high-intensity, high-specification emission reduction targets of mandatory environmental regulations have forced non-compliant enterprises to restructure energy-intensive industries, cut expenses to upgrade equipment and reduce pollution [2] (pp. 92–102). This has included reducing employee salaries, decreasing workforce numbers, and even laying off low-skilled laborers. Heavy-polluting industries in the primary and secondary sectors have suffered significant losses in “brown industrial chains,” accompanied by severe unemployment [3] (pp. 123–137).

Incentive-based environmental regulations leverage market initiative and flexibility to guide enterprises toward energy conservation and emissions reduction, accelerating transformation and upgrading [4] (pp. 156–169) to achieve carbon reduction targets. Among these, carbon trading pilot programs represent a significant incentive-based environmental regulatory measure. China’s carbon emissions trading market primarily consists of pilot markets and freely established carbon markets. The government controls the total carbon emissions quota for enterprises, which is allocated through lower-level administrative units and ultimately distributed to individual companies. If a heavily polluting enterprise exceeds its emissions quota, it must purchase additional allowances in the carbon market. Conversely, if an enterprise has surplus emissions allowances—achieved through measures like upgrading equipment or phasing out outdated industrial chains—it can sell these surplus allowances in the carbon market. In late 2011, the National Development and Reform Commission issued the “Notice on Launching Pilot Programs for Carbon Emission Trading,” designating Beijing, Tianjin, Shanghai, Chongqing, Guangdong Province, Hubei Province, and Shenzhen as pilot cities for carbon emission trading markets. This marked the beginning of China’s carbon emission trading system. In the first half of 2013, Shenzhen launched the pilot program. From the second half of 2013 to the first half of 2014, the remaining pilot provinces began establishing frameworks for their carbon trading markets. In the second half of 2016, Fujian Province was approved as a pilot province for the carbon trading market. In July 2021, the national carbon emissions trading market commenced operations, currently covering only the power generation sector. By the end of August 2024, China’s carbon emissions trading market had accumulated approximately 476 million tons of carbon emissions traded, with a transaction value reaching 27.9 billion yuan. This demonstrates the immense potential vitality of China’s carbon trading market.

In recent years, the central government has prioritized stabilizing and securing employment as a top national livelihood concern. Pollution control and environmental regulations will inevitably impact the socio-economy. Corporate transformation, upgrading, pollution reduction, and emission cuts are unavoidable. Green and low-carbon development has become mainstream, inevitably affecting the labor market. Although the carbon emissions trading market has been launched, it remains in its infancy with incomplete market development. Furthermore, the spillover effects of its pilot policies are unclear. Therefore, this paper poses the following question: Can incentive-based environmental regulation, represented by the pilot policy of carbon trading rights, achieve carbon emission reduction while promoting employment? What mechanisms underlie the impact of carbon trading pilot policies on corporate employment? Furthermore, does this policy affect only pilot provinces or does it generate spillover effects?

To address these questions, this study employs the implementation of carbon trading pilot policies as a quasi-natural experiment. It utilizes a multi-period difference-in-differences (DID) method to identify the causal relationship between carbon trading pilot policies and employment scale. This study makes the following contributions: First, unlike

previous research that primarily focused on provincial and regional levels, this paper concentrates on the micro-enterprise level to evaluate the impact of the carbon trading pilot policy—an incentive-based environmental regulation—on corporate employment. Second, building upon tests of the “scale–output effect,” “factor substitution–complementarity effect,” and “innovation compensation effect” as mediating mechanisms, this study constructs a moderated mediation model using “financing constraints” as a proxy variable. It examines the moderating role of financing constraints across these three mediating pathways, thereby enriching the understanding of the policy’s employment effects. Third, this study examines the heterogeneous impacts of the pilot policy implementation across different industries and enterprise types, as well as the talent selection preferences of enterprises within the pilot scope. This reflects enterprises’ choices and progress in upgrading and transformation. Fourth, this study is the first to examine regional and industry-level labor flows resulting from the pilot policy at the micro-enterprise level, verifying the spillover effects of the pilot policy at the enterprise level.

2. Literature Review

In the 1970s, Western nations grappled with the severe consequences of environmental pollution stemming from high industrialization. Following the implementation of a series of stringent environmental regulations, research on ecological conservation, green and low-carbon development, and transformative growth began to take shape, gradually connecting with studies on the labor market. Neoclassical economics posits that environmental regulations negatively impact labor markets, as inappropriate regulatory policies force the selection and elimination of enterprises across different industries, thereby affecting employment [5] (pp. 50–65). With social progress and evolving times, scholars have proposed alternative perspectives. Since the 1990s, Porter et al. [6] (pp. 97–118) proposed the renowned “Porter Hypothesis,” suggesting that under reasonable conditions, environmental regulation policies can stimulate corporate R&D for new products, generating an innovation compensation effect. The theory of ecological modernization posits that appropriate external regulatory systems can encourage the development of technological innovations, promote industry competition, thereby addressing environmental pollution issues, and drive the transition of production systems towards a greener direction [7] (pp. 33–44). Carraro et al. [8] (pp. 141–181) first introduced the “dual dividend hypothesis,” studying the policy effects of implementing a carbon tax in Europe. They found that imposing a carbon tax alongside fiscal policy reforms could achieve dual growth in environmental protection and employment. This “double dividend hypothesis” has received partial support [9,10] (pp. 265–295; pp. 63–79), yet some scholars persist in the view that environmental regulations reduce employment levels [11,12] (pp. 1175–1219; pp. 188–202), while others contend that environmental regulations have no significant impact on employment [13,14] (pp. 412–436). Foreign research on the employment effects of environmental regulations remains inconclusive.

Compared to other nations, China’s distinct developmental stage, industrial structure, and policy orientation create unique domestic conditions. Chinese scholars researching environmental regulations and employment predominantly focus on domestic realities. Chen Yuanyuan [15] (pp. 67–73) analyzed industry data and found that environmental regulations promote employment. Lu Yang [16] (pp. 42–54) simulated the impact of carbon taxation on Chinese employment using an autoregressive model, concluding that carbon taxes struggle to achieve dual benefits of emissions reduction and employment growth in the short term. Yu Donghua et al. [17] (pp. 35–53), analyzing panel data from China’s manufacturing sector, found environmental regulations cause “brown unemployment” by impacting high-pollution, high-emission industries while more strongly promoting

demand for skilled labor. Zhang Caiyun et al. [18] (pp. 131–146) examined the employment effects of China’s clean production standards, concluding they fostered employment at the enterprise level. Wang Feng et al. [19] (pp. 81–99) examined low-carbon city pilot programs, finding that these policies reduced urban carbon emissions while boosting employment at both the enterprise and city levels. Zhou Yahong et al. [20] (pp. 104–120) analyzed the “Ten Thousand Enterprises Energy Conservation and Low-Carbon Action” policy using a continuous DID model, revealing that while the policy reduced employment in polluting enterprises, it facilitated labor transfers at the city and industry levels. Mao Qilin et al. [21] (pp. 86–103) examined ESG’s impact on employment at the micro-firm level, finding that firms with ESG advantages showed more pronounced employment growth benefits in labor-intensive and heavily polluting industries. Wei Ping et al. [22] (pp. 18–31) constructed a two-sector model for heavily polluting and non-heavily polluting industries, testing sample-specific pathways of green governance’s impact on employment across different sectors. Wang Jie et al. [23] (pp. 156–164) employed a difference-in-differences model to find that the pilot policy boosted employment rates in pilot regions, accelerating labor mobility between urban and rural areas, sectoral shifts, and gender transitions.

After over a decade of pilot policy exploration and development, carbon emissions trading has become a crucial pathway for reducing carbon emissions [24] (pp. 49–58). Current literature on carbon trading market pilot policies predominantly focuses on inter-provincial carbon reduction effects. These pilot policies demonstrate significant carbon reduction impacts [24,25] (pp. 49–58; pp. 29–35) alongside spatially dynamic policy spillover effects [26] (pp. 26–36), while also exerting positive influences on corporate green innovation [27] (pp. 37–47).

Based on the above literature review, conclusions regarding the impact of environmental regulations on employment remain inconsistent, with diverse findings and no unified consensus at present. Research on carbon trading pilot policies has primarily focused on carbon reduction aspects, with relatively limited discussion on their employment effects.

3. Mechanism Analysis and Research Hypotheses

3.1. Environmental Regulation and Corporate Employment

Environmental regulations, as policy instruments implemented by governments, ultimately serve to maintain social stability and promote the green and healthy development of the national economy [28] (pp. 95–102). Incentive-based environmental regulations encompass carbon taxes and pilot carbon emissions trading schemes. China has yet to implement a carbon tax, and research on the employment impacts of carbon trading pilot programs remains limited. The implementation of carbon emissions trading pilot policies marks the first step in establishing China’s carbon market. It facilitates the green transformation of heavily polluting and high-carbon enterprises, advances the development of green industrial chains, stimulates corporate innovation, overcomes technological barriers, and ultimately expands corporate output [29] (pp. 1–47). Enhanced corporate production capacity increases labor demand while simultaneously creating new positions and driving “green employment” [30] (pp. 1–50). Carbon trading pilot programs also improve regional environments and expand labor supply. Based on this analysis, Hypothesis H1 is proposed.

H1. *Carbon trading pilot policies exert a positive impact on employment at the enterprise level.*

3.2. Three Intermediary Pathways

Existing mechanism studies primarily focus on three fundamental intermediary effects: the “output scale effect,” the “factor substitution and complementarity effect,” and the “innovation compensation effect”—three basic transmission mechanism effects [18,20]

(pp. 131–146; pp. 104–120). The three mechanisms are described below: (1) Pilot carbon emissions trading policies prompt changes in corporate production decisions. To avoid unnecessary “carbon purchase” expenditures, enterprises must pursue “carbon reduction” internally. Driven by profit maximization and varying adjustment difficulties across enterprise types when facing policy shocks, their strategic responses differ [19] (pp. 81–99). Firms may reduce output to lower overall energy consumption and carbon emissions, potentially decreasing employment. Alternatively, they may increase output to ensure profits fully offset the cost of purchasing carbon allowances, potentially leading to employment growth. (2) After implementing environmental regulations, the relationship between labor and capital becomes uncertain—it may be substitutive or complementary. After establishing and operating a carbon trading market, firms may invest in advanced equipment to improve technology and reduce pollution, potentially cutting labor to lower costs. Alternatively, they may increase capital and labor inputs to pursue higher profits and offset losses from environmental regulations. (3) According to the “Porter Hypothesis,” implementing reasonable and stringent environmental regulations in an appropriate context can stimulate corporate innovation to offset compliance costs. During innovation, enterprises may develop new industrial chains and improve production technologies, thereby creating new job demands [30] (pp. 1–50). Hypothesis H2 is proposed.

H2. *The pilot carbon trading policy primarily affects employment through three pathways: “output scale,” “factor substitution and complementarity,” and “innovation compensation”.*

3.3. The Moderating Role of Financing Constraints

This paper draws upon Fazzari’s theory of financing constraints, adding a moderating mechanism for financing constraints to the aforementioned transmission mechanism. Financing constraints play a pivotal role in corporate labor hiring. Due to inherent information opacity within firms and market imperfections, investors perceive risks in assessing their operational performance and corporate governance. This leads to restrictions on external financing, thereby generating financing constraints. Higher financing constraints limit green investments, dampening managers’ incentives for energy conservation and emissions reduction, thereby affecting carbon reduction [31] (pp. 69–78). Simultaneously, stronger financing constraints impose greater limitations on employment scale [21] (pp. 86–103). To date, no studies have examined the role of financing constraints in shaping employment impacts during carbon market pilot programs. Below, we analyze the moderating effects of financing constraints through three pathways: “output scale,” “factor substitution and complementarity,” and “innovation compensation”: (1) Following environmental regulation implementation, firms adjust output scale to achieve dual goals of energy conservation and emission reduction while maximizing profits. Financing constraints limit firms’ ability to expand production scale, thereby affecting workforce size. (2) Under the “factor substitution and complementarity” pathway, enterprises invest in production model upgrades to improve equipment and working environments. Financing constraints limit capital investment, thereby restricting the substitution and complementarity effects between capital and labor. (3) Faced with environmental regulation shocks, firms may pursue innovation and R&D to boost total factor productivity, thereby maintaining or exceeding previous profit levels. This process may create new positions or increase demand for technical roles. However, financing constraints reduce innovation investment, negatively impacting employment. Hypothesis H3 is proposed. We have illustrated the mechanism of action as shown in Figure 1.

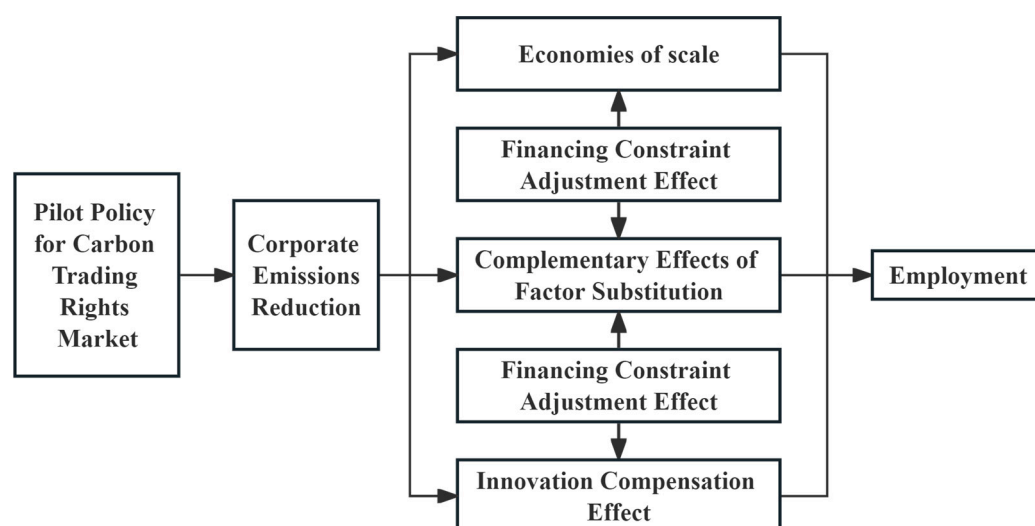


Figure 1. Mechanism of Carbon Trading Pilot Policies' Impact on Corporate Employment.

H3. *Financing constraints negatively mediate the effects of environmental regulation on output scale, factor substitution and complementarity, and innovation compensation.*

3.4. Heterogeneous Effects of Carbon Reduction Policies on Corporate Employment

In studies examining the effectiveness of carbon emission reductions, the pilot carbon trading policy has undoubtedly demonstrated significant impacts, accompanied by regional spillover effects [26] (pp. 26–36). Regarding the employment effects of carbon trading pilots, research on spillover effects remains limited and primarily focuses on static interprovincial panel data [23] (pp. 156–164). Regarding environmental regulations' effects on different industries, intensity levels of enterprises, and recruitment preferences for various talent types, existing research indicates that environmental regulations exert a greater impact on pollution-intensive enterprises [32] (pp. 146–158) and more significantly stimulate demand for skilled labor [17] (pp. 35–53). This study examines whether carbon trading pilot policies affect employment and talent recruitment patterns across different intensity levels and industries. Consequently, Hypotheses H4 are proposed.

H4. *Carbon trading pilot policies promote employment in the secondary industry and for technical talent.*

4. Empirical Model and Data Description

4.1. Policy Background

The establishment of China's carbon trading market system began with the issuance of the Implementation Rules for the Notice on Launching Pilot Carbon Emission Trading Programs in October 2011. Subsequently, pilot carbon trading programs were successively launched in Shenzhen, Beijing, Tianjin, Shanghai, Guangdong Province, Hubei Province, Chongqing Municipality, and Fujian Province in April, November, and December 2013; April and June 2014; and December 2016. This paper defines the policy implementation period as a six-month window: if pilot programs run from January to June of year t , then year t is considered the policy implementation year; if pilot programs run from July to December of year t , then year $t + 1$ is considered the policy implementation year.

4.2. Empirical Model

This study employs a propensity-score-based difference-in-differences (DID) approach to examine the impact of this carbon reduction policy on employment. The model used is as follows:

$$employ_{itj} = \alpha_0 + \alpha_1 treat_i \times post_t + \alpha_2 controls_{itj} + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (1)$$

where the dependent variable $employ_{itj}$ represents the annual number of employees at the firm in year y and is log-transformed; The explanatory variables include the *did* interaction term; $treat_i$ is the dummy variable for policy implementation: 1 if the firm is located in a pilot province, 0 otherwise; $post_t$ is the time dummy variable: 0 before the pilot start date, 1 thereafter. η_i represents the individual fixed effect; θ_t denotes the time fixed effect; λ_j indicates the industry fixed effect; μ_{itj} is the firm-level random disturbance term, with error clustering at the individual level.

Following the existing literature, the mediator variables are selected as follows: *lnoutput* scale effects are measured using enterprise revenue, represented by the logarithm of operating income [18] (pp. 131–146); *lnsub* factor substitution and complementarity effects are represented by the logarithm of the ratio of capital intensity to labor intensity [33] (pp. 62–71); innovation compensation effects are expressed through the number of R&D personnel, enterprise innovation capability, and total factor productivity *TFP* [20] (pp. 104–120). The moderator variable *WW* is measured using the financing constraint index [21] (pp. 86–103). Control variables are categorized into three dimensions: corporate finance, corporate governance structure, and regional context [19,34] (pp. 81–99; pp. 54–64). At the corporate finance level, the following control variables are selected: firm size, represented by the logarithm of total assets; debt-to-asset ratio *Lev*, expressed as total liabilities divided by total assets; return on assets (*ROA*), calculated as total profits divided by average assets; *Tobin Q*, measuring long-term growth potential; company establishment time *FirmAge*, measuring the duration of corporate development; average employee salary *lnwage*, represented by the logarithm of the annual average employee wage; fixed asset ratio *FIXED*, calculated as the ratio of fixed assets to total assets; and so on. At the corporate management level, the following were selected as control variables: dual role integration *Dual*, indicating whether the chairman and general manager positions are held by the same individual (1 if yes, 0 if no); controlling shareholding ratio of the top five shareholders *TOP5*; Management expense ratio *Mfee*. At the regional level, the following control variables were selected: Per capita indicators for each province GDP; Industrial upgrading, *Up*, defined as the proportion of secondary and tertiary industries in regional GDP; government budget expenditure, *Gc*, represented by the ratio of general government budget expenditure to regional GDP.

4.3. Sample Selection and Data Sources

This study primarily utilizes panel data from Shanghai and Shenzhen A-share listed companies between 2007 and 2022 as its research sample. Corporate-related data primarily originates from the Guotai Min'an Database and Wind Database, while provincial data mainly comes from successive editions of the China Statistical Yearbook and the official website of the National Bureau of Statistics. To mitigate the impact of outliers, the original data underwent the following processing: (1) exclusion of financial sector enterprises; (2) Exclusion of companies with ST, ST*, or similar listing statuses; (3) filling in missing values using linear interpolation. After these data treatments, an unbalanced panel comprising 4347 listed companies and 42,187 data points was obtained. The study identified the commencement dates of policy pilot programs as 2013, 2014, and 2017 based on their implementation schedules. Table 1 presents descriptive statistics for all variables.

Table 1. Descriptive Statistics.

	Variable	Obs	Mean	Std.dev	Min	Median	Max
Dependent variable	Inum	42,147	7.607	1.267	0.000	7.536	13.253
Explanatory variable	did	42,187	0.291	0.454	0.000	0.000	1.000
Mediating variable	Inoutput	42,184	21.434	1.501	10.170	21.280	28.830
	Insub	42,110	12.538	1.210	4.127	12.536	22.121
	R&D num	35,728	0.054	0.248	−7.572	0.020	5.891
	Innovation	42,158	1.564	1.639	0.000	1.386	9.358
	TFP_LP	38,005	8.329	1.070	4.252	8.229	13.106
Moderating variable	WW	36,856	−1.160	24.693	−4712.153	−1.009	−0.146
Control variables	Size	41,879	22.135	1.289	18.394	21.931	28.615
	Lev	41,844	0.425	0.205	0.015	0.418	1.718
	ROA	41,850	0.045	0.063	−0.931	0.042	1.285
	TobinQ	41,594	2.022	1.314	0.625	1.608	25.506
	FirmAge	42,187	2.859	0.379	0.000	2.890	4.174
	Inwage	42,131	0.273	1.144	−8.474	0.398	7.911
	FIXED	42,186	0.213	0.161	0.000	0.179	0.928
	Dual	42,187	0.282	0.450	0.000	0.000	1.000
	Top5	41,484	0.542	0.151	0.078	0.542	0.984
	Mfee	42,185	0.160	13.756	−0.757	0.069	2824.511
	PGDP	42,187	77,564.575	40,167.291	7778.000	69,676.000	190,000
	Up	42,187	0.935	0.047	0.713	0.951	0.998
	Gc	42,187	0.175	0.097	0.061	0.157	1.354

5. Empirical Findings and Analysis

5.1. Reference Regression Results

Table 2 presents the test results for the impact of carbon trading pilot programs on employment in listed companies within pilot cities and provinces. Column (1) shows the results without additional control variables or fixed effects. The coefficient for the core explanatory variable *did* is 0.075, which is significant at the 1% level. Column (2) omits control variables, fixed year effects, and firm effects, with results passing the 1% significance test. Column (3) includes control variables while fixing firm and time effects, and Column (4) incorporates industry fixed effects, passing significance tests at the 5% and 1% levels, respectively. After controlling for additional variables, the policy dummy coefficient decreases, indicating that control variables contain factors influencing listed firms' employee numbers. These findings collectively demonstrate that the carbon trading pilot policy boosted employment among listed companies in pilot cities. Firms within the pilot policy scope experienced a 6.4% increase in employment levels compared to those outside the pilot. Hypothesis H1 is thus validated.

5.2. Parallel Trend Test

A prerequisite for conducting a multiple-period double difference analysis is satisfying the parallel trend assumption: the trend changes of enterprises in pilot cities and non-pilot cities should be parallel before the policy implementation, while significant differences and divergences should emerge between the two groups after the policy is implemented. Building upon Model (1), this paper refines the approach by replacing the time dummy

variable with annual dummy variables for each year. The following Model (2) is constructed to test for parallel trends.

$$employ_{itj} = \alpha_0 + \alpha_1 \sum_{-4}^6 treat_i * post_t + \alpha_2 controls_{itj} + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (2)$$

Table 2. Baseline Regression.

	(1)	(2)	(3)	(4)
	lnum	lnum	lnum	lnum
did	0.075 *** (0.0136)	0.122 *** (0.0329)	0.060 ** (0.0247)	0.064 *** (0.0239)
_cons	7.586 *** (0.0073)	7.087 *** (0.0278)	−8.549 *** (0.3980)	−8.780 *** (0.3776)
Controls	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes
Symbol FE	No	Yes	Yes	Yes
Ind FE	No	No	No	Yes
Observations	42,147	42,147	39,542	39,542
R ²	0.001	0.155	0.928	0.930

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

The value is 1 if the city where the firm i is located implemented the pilot policy in a given year and 0 otherwise. Considering the limited data available for the four periods preceding the policy timeline and the six years following policy implementation, the data from the four years prior to policy implementation were aggregated into period-4, with period-3 designated as the base period. Data from the six years after policy implementation were aggregated into period 6. Figure 2 presents the results of the parallel trend test. This indicates that prior to policy implementation, there was no significant difference in employee numbers between the two groups. After policy implementation, a significant difference emerged between pilot city enterprises and non-pilot enterprises in terms of employee numbers, demonstrating a significant upward trend in employment levels driven by the carbon trading pilot policy. Therefore, the parallel trend test is passed.

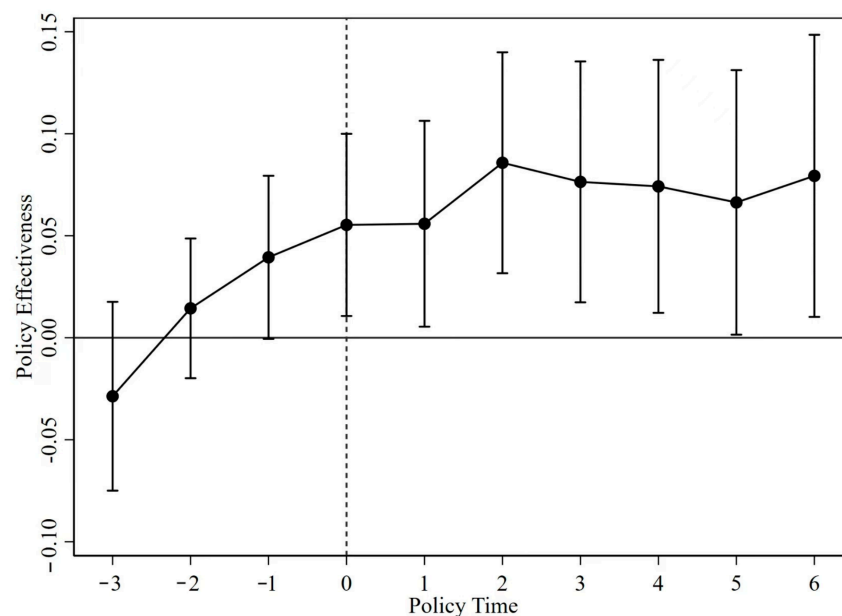


Figure 2. Parallel Trend Test Result.

5.3. Placebo Test

To determine whether the model can accurately distinguish between the experimental and control groups and avoid systematic bias, this study conducted 500 random sampling tests and re-estimated the regression model to examine the distribution of coefficients and p -values. The test results are shown in Figure 3. The coefficient estimates for the policy dummy variable clustered around zero and approximated a normal distribution. The coefficient distribution in the benchmark regression diverged significantly from that of the random sampling regression coefficients. Therefore, the benchmark regression results in this study can be considered free of systematic bias.

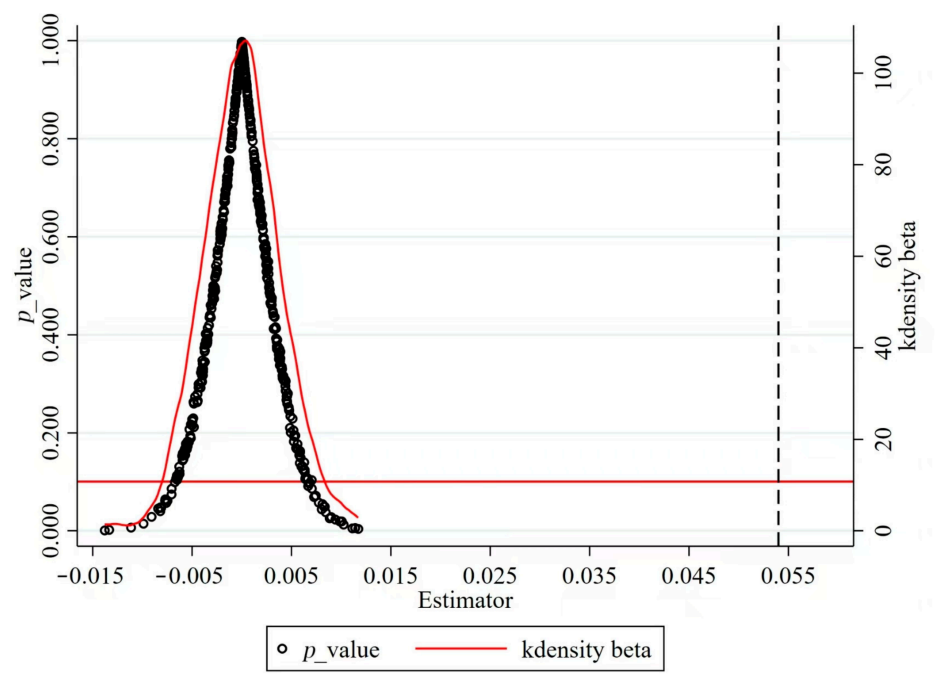


Figure 3. Placebo Test Result.

5.4. Robustness Test

5.4.1. Propensity Score Matching (PSM)

To mitigate sample selection bias, this study employs 1:1 nearest neighbor propensity score matching without replacement, thereby dividing the sample into experimental and control groups with covariates as control variables. Parameter estimation is conducted on the matched samples. The regression results are presented in Column (1) of Table 3, where the explanatory variable coefficient is significantly positive. This indicates that sample selection bias does not affect the study conclusions in this context.

5.4.2. Replace the Dependent Variable, Reduce the Sample Interval, and Reduce the Tail by 1%

The measurement method for enterprise employment was modified by replacing the dependent variable. The enterprise personnel count was substituted with year-end employment figures, which were then log-transformed [20] (pp. 104–120). The sample period was set to 2010–2019. Column (2) in Table 3 presents the parameter estimates after replacement, while column (3) shows the estimates without replacement. The fourth column is the result with a 1% reduction in front and back. The coefficients of the core explanatory variables are all positive and have passed the significance test at the 1% level.

Table 3. Robustness Test Results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	lnum	lnempl	lnum	lnum	did	lnum	lnum	lnum	lnum
CPRI					−0.002 *** (0.000)				
did	0.059 ** (0.0278)	0.056 *** (0.0191)	0.049 *** (0.0188)	0.063 *** (0.0236)		1.022 *** (0.349)	0.074 *** (0.0231)	0.058 *** (0.0217)	0.064 *** (0.0236)
_cons	−7.967 *** (1.6041)	−9.302 *** (0.9013)	−9.425 *** (0.8669)	−8.962 *** (0.7417)			−8.852 *** (0.8008)	−9.097 *** (0.7184)	−9.104 *** (0.7233)
Controls/ Year/Symbol/ Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,460	23,787	23,787	39,542	39,108	39,108	29,927	39,538	39,542
R ²	0.955	0.947	0.945	0.929		0.303	0.930	0.930	0.930
Phase 1 F-value					51.96				

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

5.4.3. Instrumental Variables Method

When using multi-period DID to examine the impact of carbon trading pilot policies on market employment, the ideal scenario assumes no other factors influencing employment, with the pilot policy being the sole channel. However, this is not the case. The provinces and cities selected for the pilot program are predominantly more developed regions with a higher GDP, and their reliance on different industries varies. Furthermore, unobserved firm-level variables—i.e., omitted variables—may also introduce bias into the estimation results. Therefore, following Tsoutsoura [35] (pp. 649–688), this study employs the instrumental variables method to address endogeneity concerns.

According to the selection principles of the instrumental variable method, two basic conditions, namely, exogenousness and correlation, must be adhered to. This paper refers to Guo, K., Ji, Q., Zhang D.Y. (2024) [4] and selects the threshold method to construct the Provincial Climate Physical Risk Index (CPRI) as an instrumental variable. CPRI can represent the frequency of extreme climate impacts experienced by different regions and is a result of climate change. The pilot policy of carbon trading rights, as a representative of incentive-based environmental regulation policies, is assigned the task of limiting the exacerbation of climate change. Frequent extreme climate events accelerate the speed of enacting environmental regulation policies. However, as a pilot policy, the carbon trading rights market is not perfect and the impact on corporate economics is uncertain. Therefore, pilot regions may be more inclined to those with less impact from climate change, and the carbon trading market system will only be promoted nationwide after it becomes more mature. From the above analysis, it can be seen that this index is related to the pilot policy of carbon trading, satisfying the correlation assumption. Secondly, CPRI is unrelated to some unobservable variables of enterprises and does not directly affect enterprise employment, satisfying the exogenousness assumption. In Table 3, column (5) presents the regression results of the first stage, where the coefficient of the explanatory variable is significantly negative at the 1% level, and the F statistic is significantly greater than 10, consistent with our analysis. Column (6) presents the regression results of the second stage, indicating that after addressing endogeneity issues, the dummy explanatory variable remains significantly positive and passes the significance test at the 1% level. This suggests that the pilot policy of carbon trading can significantly enhance the vitality of the employment market and promote employment.

5.4.4. Excluding Concurrent Policies

During the sample period, multiple domestic policies may have exerted similar effects on corporate employment, potentially introducing errors. This study selects the “Low-Carbon City” pilot program and the “Announcement on Implementing Special Emission Limits for Air Pollutants” as policies requiring exclusion. Dummy variables for these policies are added to the original baseline regression model: the variable ‘city’ is set to 1 if the firm’s city was a low-carbon pilot city that year, and 0 otherwise; the variable ‘area’ is set to 1 if the firm’s city was a key air pollution control zone that year, and 0 otherwise. The parameter estimates after controlling for contemporaneous policies are shown in column (7) of Table 3. Even after controlling for these policies, the policy dummy variables remain significantly positive, indicating that the carbon trading pilot policy has a clear positive effect on corporate employment.

5.4.5. Update Enterprise Office Coordinates and Delete Missing Values

Due to the possible differences between the place of registration and the place of production of enterprises, the pilot policy of carbon trading rights has a greater impact on the production site. We determined the pilot enterprise and the policy dummy variable *did1* according to the office location of listed companies and conducted a benchmark regression test. The results are shown in column (8) of Table 3; the explanatory variable is 0.058 and is significantly positive at the 1% level. Even if there is a difference between the actual office and the registered place of the enterprise, it does not affect the significance of the impact of the pilot policy on enterprise employment. The missing value was deleted, and the estimated value of the coefficient was significantly positive at the 1% level, which verified the robustness of the results.

5.4.6. Effect Estimation Using Other Heterogeneity Treatments

Due to the heterogeneity of the estimation results of the multiphase did model, which varies with the group and time dimension, the estimation results are biased. Therefore, this paper refers to the Bacon decomposition method proposed by Goodman-Bacon (2021) [36] (pp. 254–277) to process the model, which is divided into a treatment group, control group and untreated group. To avoid treatment effect differences, this paper adopts the method of Callaway and Sant’Anna [37] (pp. 200–230) and employs CS-DID to re-examine the impact of the carbon trading pilot policy on corporate employment. Companies in non-pilot regions are designated as the never-treated group, while companies that have not reached the pilot implementation year are designated as the not-yet-treated group. Table 4 shows the results of Bacon decomposition. It can be seen from the results that the weight of the treated group and the untreated group accounted for 81.7%, and the weight of the other three groups at different time points accounted for 18.3%. Therefore, most of the impacts of carbon trading rights pilot policies on the labor market come from the “treatment group” and “untreated group”, which shows that the parameter estimation made in the previous paper is reliable, and the error of the estimation results due to the heterogeneous treatment effect is small. Table 5 shows the test results of cs-did. The results in column (2) show that the dynamic average processing effect is significant. The carbon trading pilot policy promotes the employment of Listed Companies in the pilot area, which is consistent with the benchmark regression results, and the robustness test passes.

Table 4. Bacon Decomposition.

Project Category	Weighting Factors	Estimated Average DID Coefficient
Pre-treatment group vs. Post-control group	0.018	0.057
Post-treatment Group vs. Pre-control Group	0.027	−0.019
Treated group vs. Untreated group	0.817	0.128
Treatment Group vs. Control Group	0.138	−0.025
DID Estimation Results		0.102

Table 5. CS-DID.

	(1)	(2)	(3)	(4)
	ATT	Dynamic ATT	Calendar Time ATT	Group ATT
Simple ATT	0.108 *** (0.0265)			
Pre_avg		0.013 (0.0090)		
Post_avg		0.117 *** (0.0288)		
CAverage			0.099 *** (0.0243)	
GAverage				0.105 *** (0.0259)

Note: Standard errors in parentheses. *** $p < 0.01$.

5.5. Mechanism Verification

5.5.1. Mediation Effect Model

The essence of the carbon trading pilot policy lies in its role as a market-incentive-based environmental regulation, fully mobilizing governments, institutions, and enterprises to utilize the carbon emission allowance trading mechanism for the efficient allocation of carbon trading rights. To characterize the pathways through which the pilot carbon trading policy affects corporate employment, this study employs the mediation equation framework proposed by Wen and Ye [38] (pp. 731–745), supplemented by Sobel and Bootstrap tests to ensure robustness. Considering that the mediating and moderating variables selected in this paper may also be influenced by policies, a one-lag treatment was applied. To explore the moderation mechanism, we construct the following model by combining Equation (1).

$$l.mediator_{itj} = \beta_0 + \beta_1 did + \beta_2 controls + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (3)$$

$$employ_{itj} = \gamma_0 + \gamma_1 did + \gamma_2 l.mediator_{itj} + \gamma_3 controls + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (4)$$

Drawing on prior literature, this study examines the mechanism through which carbon trading pilot policies influence the labor market primarily via three types of mediating effects: “scale output,” “factor substitution,” and “innovation compensation.” It also explores the moderating mediating effect of increased financing constraints.

In columns (1), (2), (3) of Table 6 examining output effects, regression results indicate that coefficient estimates for both core explanatory variables and mediating variables are significantly positive, with Sobel and Bootstrap tests passing. Firms located in carbon trading pilot cities exhibit markedly higher operating revenues and significantly increased output compared to those in non-pilot cities. Compared to Column (1), the coefficient value of the policy dummy variable decreases, indicating that firm output exerts an indirect mediating effect.

Table 6. Mechanism Verification-1.

	(1)	(2)	(3)	(4)	(5)
	Inum	L. Inoutput	Inum	L. Insub	Inum
did	0.064 *** (0.0239)	0.073 *** (0.0188)	0.039 * (0.0226)	−0.059 * (0.0307)	0.040 ** (0.0198)
L. Inoutput			0.204 *** (0.0123)		
L. Insub					−0.254 *** (0.0132)
_cons	−8.780 *** (0.3776)	2.239 *** (0.6027)	−9.441 *** (0.7304)	5.190 *** (0.8176)	−7.619 *** (0.6457)
Controls/Year/Symbol/Ind FE	Yes	Yes	Yes	Yes	Yes
Observations	40,607	34,496	34,496	34,434	34,434
R ²	0.925	0.943	0.937	0.838	0.943
Sobel test			3.795 ***		1.922 **
Bootstrap Test			6.07 ***		3.67 ***

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Columns (1), (4), and (5) examine factor substitution and complementarity. In Column (4), the policy dummy variable *did* is significantly negative at the 5% level, while in Column (5), *did* is significantly positive at the 5% level. The mediating variable *Insub* is significantly negative at the 1% level and passes both Sobel and Bootstrap tests. After incorporating the third variable, the coefficients of the core explanatory variables increase. Since the coefficient estimates for the explanatory variables in Column (4) and Column (5) *Insub* are both significantly negative, factor substitution and complementarity continue to exert an indirect mediating effect. This indicates that the implementation of the carbon trading pilot policy promotes corporate employment scale and enhances employment levels. However, this effect is mitigated by the role of factor substitution and complementarity—specifically, capital substituting for labor exerts a negative indirect mediating effect. Nevertheless, the positive direct effect generated by the carbon trading pilot policy proves more effective.

In examining the innovation compensation mechanism, this paper first investigates the policy's impact on corporate R&D expenditure, then assesses its effect on corporate innovation capacity, and finally evaluates its influence on corporate upgrading. As shown in columns (2) and (3) of Table 7, the policy exerts a significant positive effect on the number of personnel allocated to corporate R&D. Column (4) shows negative coefficient estimates for the policy dummy variable, while column (5) reveals positive estimates that pass the 5% significance level test. Firm innovation capacity exhibits a masking effect on employment. Column (6) uses total factor productivity (TFP), measured via the LP method, as a proxy for firm upgrading. The core explanatory variable is significantly positive and passes the 1% significance level test. The regression results indicate that after implementing the carbon trading rights policy, enterprises' total factor productivity significantly improved. All estimation results passed Sobel tests and Bootstrap tests, confirming the robustness of the mediating mechanism. The carbon trading pilot policy positively impacts enterprise employment through innovation compensation. Hypothesis H2 is supported.

Table 7. Mechanism Verification-2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Inum	L. R&D Num	Inum	L. Innovation	Inum	L. TFP_LP	Inum
did	0.064 *** (0.0239)	0.020 * (0.0107)	0.073 *** (0.0252)	−0.131 *** (0.0411)	0.056 ** (0.0235)	0.059 *** (0.0185)	0.042 * (0.0255)
L. R&D num			0.199 *** (0.0571)				
L. Innovation					0.018 *** (0.0038)		
L. TFP_LP							0.093 *** (0.0134)
_cons	−8.780 *** (0.3776)	−2.083 *** (0.4491)	−8.708 *** (0.8610)	−3.669 *** (1.2365)	−8.908 *** (0.7508)	−3.115 *** (0.6028)	−8.599 *** (0.7903)
Controls/Year/ Symbol/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,607	29,950	29,950	34,540	34,540	31,047	31,047
R ²	0.925	0.717	0.936	0.774	0.933	0.909	0.935
Sobel test			1.669 *		−2.621 ***		2.904 ***
Bootstrap Test			3.66 ***		−4.37 ***		4.42 ***

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.5.2. Moderation-Mediated Effect Model

To further examine the moderating effect of financing constraints on the mediating effect, a stepwise regression approach [39] (pp. 714–726) was employed to construct the following moderated mediation model:

$$employ_{itj} = \alpha_0 + \alpha_1 did + \alpha_2 l.moderator_{itj} + \alpha_3 did * l.moderator_{itj} + \alpha_4 controls_{itj} + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (5)$$

$$l.mediator_{itj} = \beta_0 + \beta_1 did + \beta_2 l.moderator_{itj} + \beta_3 did * l.moderator_{itj} + \beta_4 controls_{itj} + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (6)$$

$$employ_{itj} = \gamma_0 + \gamma_1 did + \gamma_2 l.moderator_{itj} + \gamma_3 did * l.moderator_{itj} + \chi_1 l.mediator_{itj} + \chi_2 l.mediator_{itj} * l.moderator_{itj} + \eta_i + \theta_t + \lambda_j + \mu_{itj} \quad (7)$$

Based on the previous discussion on the mediating effect path, this paper chooses to use the financial constraints index WW as an indicator to assess the degree of corporate financial constraints. In the evaluation of the “innovation compensation” path, corporate innovation capability is selected as the proxy variable for this mediating effect. In Formula (5), the direct effect of policy is $\alpha_1 + \alpha_3 moderator$. If α_3 is significant, then financial constraints have a moderating effect on the direct effect. The mediating effect can be divided into two paths: the first from the independent variable to the mediating variable, and the second from the mediating variable to the dependent variable. According to Formulas (6) and (7), the mediating effect should be $(\alpha_1 + \alpha_3 moderator)(\chi_1 + \chi_2 moderator)$. If α_3 is significant and χ_2 is not significant, then financial constraints have a moderating effect on the first half of the path; if α_3 is not significant and χ_2 is significant, then financial constraints have a moderating effect on the second half of the path; when both α_3 and χ_2 are significant, then financial constraints exert a moderating effect on the entire mediating path; only when both α_3 and χ_2 are not significant, do financial constraints not have a moderating effect.

In Table 8 column (1), the estimated coefficient of the interaction term between did and financing constraints WW is significant at the 5% level, indicating that financing constraints negatively moderate the direct effect of the carbon trading market pilot policy

on enterprise employment. The estimated coefficient of the interaction term between did and WW in column (2) is significantly negative, while the estimated coefficient of the interaction term in column (3) is not significant. Therefore, on the mediating effect path of “output scale”, financing constraints play a negative moderating role and affect the first half of the path from the policy explanatory variable to lnoutput, that is, under the impact of the carbon trading pilot policy, enterprises with stronger financing constraints have lower output. This may be because enterprises facing financing difficulties find it more difficult to maintain their original output in the face of policy shocks. The estimated coefficient of the interaction term in column (4) is -0.011 and significant at the 1% level, and the interaction term between lnsub and WW in column (5) is significantly negative at the 1% level. Therefore, on the mediating path of “factor substitution complementarity”, financing constraints play a negative moderating role on both the front and back paths, that is, under the impact of the carbon trading rights pilot policy, enterprises with tight financing find it more difficult to replace capital and labor factors and instead maintain their labor employment. This may be because under the policy, enterprises’ funds are restricted and bank lending becomes more difficult, thereby reducing the substitution of capital for labor. The interaction term between did and WW in column (6) and the interaction term between the mediating variable enterprise innovation capability and WW in column (7) both fail to pass the significance test. Therefore, on the mediating path of “innovation compensation”, financing constraints do not play a moderating role; that is, financing constraints do not affect the path through which carbon trading policy pilots influence employment through enterprise innovation. Hypothesis H3 is established.

Table 8. Moderation-mediated effect test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnum	L. lnoutput	lnum	L. lnsub	lnum	L. Innovation	lnum
did	0.044 *	0.035 *	0.037	-0.070^{**}	0.013	-0.133^{***}	0.048^{**}
	(0.0239)	(0.0212)	(0.0227)	(0.0308)	(0.0173)	(0.0423)	(0.0236)
L. WW	-0.000	-0.000^{***}	0.000	0.000^{***}	0.007^{***}	-0.000	-0.000
	(0.0000)	(0.0000)	(0.0012)	(0.0000)	(0.0008)	(0.0000)	(0.0000)
did $\times$ L. WW	-0.010^{**}	-0.040^{***}	-0.002	-0.011^{***}	-0.007^{*}	-0.002	-0.009^{***}
	(0.0042)	(0.0109)	(0.0023)	(0.0020)	(0.0039)	(0.0108)	(0.0029)
L.lnoutput			0.207^{***}				
			(0.0132)				
L. lnoutput $\times$ L. WW			-0.000				
			(0.0001)				
L. lnsub					-0.525^{***}		
					(0.0195)		
L. lnsub $\times$ L. WW					-0.001^{***}		
					(0.0001)		
L. Innovation							0.011^{*}
							(0.0061)
L. Innovation $\times$ L. WW							-0.006
							(0.0044)
_cons	-8.982^{***}	2.345^{***}	-9.467^{***}	5.003^{***}	-6.316^{***}	-3.248^{**}	-8.916^{***}
	(0.8010)	(0.6077)	(0.7731)	(0.8592)	(0.5742)	(1.2841)	(0.7981)
Controls/Year/ Symbol/Ind FE	yes	yes	yes	yes	yes	yes	yes
Observations	29,487	29,486	29,486	29,447	29,471	29,483	29,483
R ²	0.930	0.943	0.933	0.832	0.961	0.773	0.930

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.6. Heterogeneity Analysis

This paper categorizes the sample based on different types of ownership, dividing enterprises into state-owned and private enterprises, and conducts separate regressions for each category. Columns (1) and (2) in Table 9 present the parameter estimates for state-owned and private enterprises, respectively. The regression result in Column (1) is positive but fails to pass the significance test, indicating that the carbon trading pilot policy has no significant impact on employment levels in state-owned enterprises. Column (2) shows a regression result of 0.061, which is significantly positive at the 5% level. This indicates that the pilot policy boosted employment in private enterprises, increasing their workforce size. A possible reason for this outcome is that state-owned enterprises possess relatively solid foundational capital strength and stable operational models, making them less susceptible to policy impacts. Private enterprises, when facing market incentive-driven environmental constraints, are more responsive and adaptable, leading to greater fluctuations in their employment levels.

Table 9. Heterogeneity Test-1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	State-Owned Enterprise	Private Enterprises	Primary Industry	Secondary Industry	Tertiary Sector	Labor-Intensive	Technology-Intensive	Capital-Intensive
did	0.046 (0.0371)	0.061 ** (0.0302)	0.279 ** (0.1349)	0.083 *** (0.0249)	−0.058 (0.0479)	0.021 (0.0370)	0.059 ** (0.0270)	0.039 (0.0538)
_cons	−6.692 *** (0.8907)	−10.155 *** (1.2930)	−9.918 *** (2.9841)	−8.697 *** (0.6870)	−9.561 *** (1.8637)	−8.495 *** (1.1527)	−8.150 *** (0.9486)	−7.483 *** (1.1496)
Controls/Year/ Symbol/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,421	25,051	503	29,009	9987	13,104	17,376	7111
R ²	0.933	0.930	0.952	0.942	0.931	0.942	0.945	0.942

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

This study categorizes the sample by industry and conducts separate parameter estimates for the primary, secondary, and tertiary sectors. Columns (3) to (5) present the regression results for these sectors respectively. The regression for the primary sector yields an estimated coefficient of 0.279, which is significantly positive at the 5% level, indicating that the pilot policy significantly promotes employment in primary sector enterprises. Column (4) presents the regression results for secondary industry enterprises. The coefficient is estimated at 0.083 and passes the 1% significance level test, indicating that the pilot policy also promotes employment in secondary industry enterprises. Column (5) shows the regression results for the tertiary industry. The coefficient estimate for the policy explanatory variable is −0.058 but fails the significance test. Therefore, it can be concluded that the pilot policy has no significant impact on the number of employees in tertiary industry enterprises. The carbon trading pilot policy primarily targets energy-intensive and carbon-emitting enterprises in the primary and secondary industries. Heterogeneity tests reveal employment growth in both sectors, consistent with prior analysis. Given fewer restrictions on tertiary enterprises, the policy exerts limited influence on this sector.

Enterprises were categorized by capital intensity into labor-intensive, technology-intensive, and capital-intensive firms, with benchmark regression analyses conducted sequentially. The parameter estimate for labor-intensive enterprises was 0.021 but failed to pass the significance test. The coefficient estimate for technology-intensive enterprises was 0.059, significantly positive at the 5% level, indicating the pilot policy had a significant positive effect on employment in technology-intensive firms. The regression result for capital-intensive enterprises was 0.039, failing to pass the significance test. Consequently, the carbon trading pilot policy has no significant impact on employment levels in labor-intensive and capital-intensive enterprises, but it has a noticeable promotional effect on

technology-intensive enterprises. Technology-intensive enterprises place greater emphasis on technological innovation and upgrading. When faced with reforms in carbon trading quota allocation, these enterprises tend to focus on improving technology, increasing R&D investment, and increasing the number of R&D personnel, thereby driving an increase in employment levels.

Observing the estimated coefficients across different industries reveals that the secondary industry exhibits the most significant effect, followed by the primary industry. We now conduct an in-depth analysis of the primary and secondary industries, further subdividing them into five sectors—agriculture, mining, manufacturing, electricity and heat supply, and construction—for additional regression analysis.

Table 10 indicates that both agriculture and manufacturing passed the significance test under policy influence, while mining, electricity and heat supply, and construction showed no significant policy impact. Since the primary sector comprises agricultural industries, the regression results align with Column (3) of Table 10, showing a positive significance at the 5% level. A possible reason is that the pilot policy of carbon trading rights promotes green transformation in pilot areas, facilitates resource reallocation, and drives the expansion of agricultural economic activities through the development of related industries and regional economies, thereby indirectly enhancing the employment level in the agricultural sector. Manufacturing constitutes the backbone of the secondary sector. The coefficient estimate in column (3) is significantly positive at the 1% level, indicating that manufacturing employment within the pilot policy scope increased by approximately 9.3% compared to manufacturing enterprises outside the pilot scope. Overall, the carbon trading pilot policy significantly boosted employment in agriculture and manufacturing while having a negligible impact on mining, electricity and heat supply, and construction.

Table 10. Heterogeneity Test-2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Agriculture	Mining Industry	Manufacturing	Electricity, Heat, and Other Supply Industries	Construction Industry	High-Carbon Manufacturing Industries	Non-High-Carbon Manufacturing Industries
did	0.279 ** (0.1349)	0.065 (0.1672)	0.093 *** (0.0247)	0.208 (0.1362)	0.071 (0.1140)	0.023 (0.0541)	0.085 *** (0.0268)
_cons	−9.918 *** (2.9841)	−6.458 (4.5107)	−8.969 *** (0.7472)	−2.557 (3.1529)	−11.851 *** (3.1506)	−9.288 *** (1.2269)	−8.376 *** (0.9096)
Controls/Year/ Symbol/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	503	723	25,467	1286	997	5544	19,908
R ²	0.952	0.964	0.943	0.909	0.966	0.954	0.943

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

Regarding the implementation details of the carbon trading pilot policy, considering the subdivisions within the manufacturing sector, this study further categorizes manufacturing into high-carbon and non-high-carbon industries [based on the 2024 State Council policy interpretation, this study designates C22, C25, C26, and C30–C32 as high-carbon industries]. Columns (6) and (7) in Table 10 reveal that the core explanatory variable of the policy is not significant in high-carbon manufacturing sectors but shows a significant positive effect in non-high-carbon sectors. This indicates that the carbon trading pilot policy promotes employment in non-high-carbon manufacturing sectors while having no significant impact on high-carbon sectors. A possible explanation for this phenomenon is that, under the moderating effects of three intermediary mechanisms and financing constraints, different industries are affected differently due to their varying transformation capabilities, technological foundations, and industrial relevance. High-carbon industries were first listed as key industries under the carbon trading pilot policy, facing the most stringent

regulatory penalties for carbon emissions and being forced to adopt various measures to “reduce carbon emissions and emissions reduction”. In existing literature research, the pilot policy of carbon emission trading rights has reduced carbon emissions in high-carbon industries (Song et al. 2021) [27], increasing investment in technological research and development, environmental management costs, and equipment upgrades, which generates new job demand. On the other hand, the simplification of production processes and equipment upgrades may replace some labor, reducing demand for traditional jobs, thus leading to an overall insignificant employment effect. Non-high-carbon industries, which face fewer restrictions on carbon emissions, can gain development opportunities through green technology research and development, industrial chain expansion, and market environment improvement under the influence of policies, showing a more pronounced positive impact on employment.

6. Further Exploration

In this section, we will examine at the enterprise level the talent selection preferences of pilot policy enterprises, labor mobility across industries, and the presence of spillover effects.

6.1. Firm Selection in Talent Hiring

Previous research has demonstrated that carbon trading pilot policies exert a significant positive effect on corporate employment. This study further examines the impact of carbon trading pilot policies on employee hiring by conducting categorical regression analyses on firms’ selection of various talent types and the number of employees across different departments. Employees holding bachelor’s degrees or higher are classified as highly educated, while others are categorized as medium or low educated. Companies are segmented into production departments, technical departments, and other departments for regression analysis.

The regression results in Table 11 indicate that the coefficient estimate for high-level education is 0.052, significant at the 1% level. Following the implementation of the pilot policy, enterprises in pilot cities hired more employees with high-level education. The coefficient estimate for low-level education is 0.018, but it fails to pass the significance test. Therefore, the pilot policy has no significant impact on enterprises’ hiring of low-level education employees. Linking this to previous findings, this phenomenon likely arises because when facing policy shocks, firms tend to respond by increasing R&D expenditures, upgrading industrial equipment, and pursuing transformation toward high-tech and high-value-added sectors. The knowledge background of highly educated talent better aligns with these corporate needs, making them more likely to hire such individuals.

In the departmental analysis, the regression result for the production department was positive but failed to pass the significance test. For the technical and other sectors, the parameter estimates were 0.024 and 0.051, respectively, and were significantly positive at the 10% and 5% levels. The pilot policy had a positive impact on increasing the number of employees in the technical and other sectors of enterprises. In line with the previous conclusions, the pilot policy had a significant positive effect on employment in technology-intensive enterprises, further validating that the pilot policy made enterprises more inclined to expand their technical workforce. This effect may stem from the pilot policy accelerating corporate transformation, thereby expanding demand for technical talent.

In summary, the carbon trading pilot policy increases corporate employment by incentivizing firms to hire more highly educated personnel and technical department staff to address policy-driven transformation, upgrading, and R&D investment. Hypothesis H4 is supported.

Table 11. Corporate Preferences for Different Types of Talent.

	(1)	(2)	(3)	(4)	(5)
	Highly Educated	Low Educational	Production Department	Technical Department	Other Departments
did	0.052 *** (0.0161)	0.018 (0.0496)	0.031 (0.0253)	0.024 * (0.0135)	0.051 ** (0.0246)
_cons	−2.690 *** (0.6455)	−5.641 *** (1.0936)	−5.681 *** (1.0693)	−2.039 *** (0.5878)	−1.941 *** (0.5940)
Controls/Year/ Symbol/Ind FE	Yes	Yes	Yes	Yes	Yes
Observations	31,745	31,745	36,323	39,132	36,085
R ²	0.906	0.888	0.847	0.865	0.781

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.2. Exploring Spatial Spillover Effects from the Perspective of Enterprises

A conclusion can be drawn from the previous section: the pilot carbon trading policy has a positive effect on enterprise employment, and the impact is more significant on personnel in the secondary industry and technology sector. This raises a question: where does the increase in employment caused by the pilot policy come from? Has it also affected the reallocation of labor resources in neighboring provinces? In this section, we will construct a multi-period DID model to discuss whether the pilot carbon trading policy has spillover effects. To exclude the possibility that the decline in employment in neighboring provinces may be due to impacts from other regions, this paper further selects non-neighboring non-pilot provinces to construct dummy variables. The models (9) and (10) are established as follows:

$$employ_{itj}^1 = \varepsilon_0 + \varepsilon_1 treat_i^1 * post_t^1 + \varepsilon_2 controls_{itj} + \eta_i + \theta_t + \lambda_j + \mu_p \quad (8)$$

$$employ_{itj}^2 = v_0 + v_1 treat_i^2 * post_t^2 + v_2 controls_{itj} + \eta_i + \theta_t + \lambda_j + \mu_p \quad (9)$$

The dependent variable $employ_{itj}^1$ represents the total number of employees in firm ‘i’ during year ‘t’. The dummy policy variable $did1$ is constructed using the explanatory variables $treat_i^1 * post_t^1$, where $treat_i^1$ indicates whether firm ‘i’'s region is an adjacent province to a pilot area, and $post_t^1$ indicates whether the pilot policy was implemented in year ‘i’. The explanatory variable in Formula (10) is the dummy policy variable $did2$ constructed from the combination of $treat_i^2 * post_t^2$, where $treat_i^2$ indicates whether the region where company ‘i’ is located is a non-pilot and non-adjacent province, and $post_t^2$ indicates whether the pilot province with a relatively short linear distance implemented the pilot policy in year ‘i’. Control variables are consistent with the preceding model. η_i , θ_t , λ_j represent fixed effects, while μ_p accounts for provincial-level error clustering. Since Shenzhen initiated its pilot program in the first half of 2013 and Guangdong Province began its pilot in the second half of 2013, this study treats the implementation time for Guangdong’s neighboring provinces not included in the pilot list—namely Jiangxi, Hunan, Guangxi, and Hainan—as 2013. Meanwhile, after analyzing non-pilot and non-adjacent provinces, it was found that the policy time $post$ was all in 2014.

Table 12 presents the parameter estimation results for models (9) and (10). The first column shows the regression results for the total number of employees, with an estimated parameter value of −0.095 that passes the significance test at the 1% level. Therefore, the implementation of the pilot policy has a significant negative impact on employment in the neighboring provinces of the pilot. After the implementation of the policy, the number of employees in enterprises in the neighboring provinces decreased by 9.3% compared to other

provinces. The second column shows the test results for non-pilot and non-neighboring provinces, where the estimated coefficient is not significant. This suggests that there is spatial adjustment after the policy shock, including the reallocation of labor resources and the relocation of enterprises or industries. Thus, the carbon trading pilot policy has a spatial spillover effect.

Table 12. Policy Spillover Effects at the Enterprise Level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Adjacent Provinces	Non-Adjacent Provinces	Primary Industry	Secondary Industry	Tertiary Sector	Labor-Intensive	Technology-Intensive	Capital-Intensive
did1	−0.095 *** (0.0238)		−0.673 *** (0.2189)	−0.099 *** (0.0285)	−0.102 *** (0.0366)	−0.136 *** (0.0396)	−0.042 (0.0285)	−0.058 ** (0.0276)
did2		−0.025 (0.0546)						
_cons	−9.034 *** (1.1411)	−8.215 *** (1.1064)	−23.364 * (13.0313)	−8.634 *** (1.2538)	−7.791 *** (1.6275)	−7.717 *** (2.2613)	−11.249 *** (1.8266)	−5.231 ** (1.9726)
Controls/Year/ Symbol/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,481	39,481	502	28,971	9967	17,711	13,646	7314
R ²	0.935	0.935	0.794	0.945	0.916	0.831	0.956	0.982

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Columns (2)–(4) present the impacts faced by different industries due to policy shocks. All three industries, namely the primary, secondary, and tertiary sectors, have experienced significant negative impacts. This indicates that the pilot policy has led to a decline in employment in the primary, secondary, and tertiary sectors in neighboring provinces. A possible reason is that the pilot policy has generated a spatial spillover effect, stimulating the vitality of the employment market in the pilot provinces. This has led to an increase in labor demand in the primary and secondary sectors, while the tertiary sector, with its large employment base and strong mobility, has seen labor migration from neighboring provinces to the pilot provinces. Consequently, there has been a trend of decreased employment in the secondary and tertiary sectors in neighboring provinces. Another possible reason is that the pilot policy for carbon trading rights has triggered the relocation of related industries or enterprises, leading to labor loss in neighboring provinces. Columns (5)–(7) present the impact of the pilot policy on employment in different types of enterprises. The coefficient estimate for technology-intensive enterprises is −0.136, which is significant at the 1% level, while the coefficient estimate for asset-intensive enterprises is −0.058, which is significant at the 5% level. This shows that the policy has had a negative impact on the employment volume of technology-intensive and resource-intensive enterprises in neighboring provinces. Combining the previous research conclusions, a possible reason for this phenomenon is that policy shocks have accelerated enterprise transformation, increasing the demand for skilled talents. The carbon trading rights market has also accelerated the flow of resources and cash, which has affected the number of employees in technology-intensive and resource-intensive enterprises in neighboring provinces.

In summary, the pilot carbon trading policy may trigger labor mobility among different provinces, industries, and types of enterprises, and there is a phenomenon of spillover effects.

7. Conclusions and Outlook

As a representative policy of market-based environmental regulation, the pilot carbon trading scheme has drawn significant attention since its inception. This paper treats the implementation of the pilot carbon trading rights policy as a quasi-natural experiment. Using

data from Chinese A-share listed companies from 2007 to 2022, it employs a multi-period difference-in-differences model to examine the policy's impact on corporate employment. A series of robustness tests and heterogeneity analyses are conducted to explore its mechanism of action. Finally, the pilot policy's effects on talent mobility and spillover effects are evaluated at the firm level.

Through this evaluation, the study draws the following key conclusions: 1. The pilot policy significantly boosted corporate employment, with private enterprises, technology-intensive firms, and secondary industry companies experiencing more pronounced positive effects. 2. The policy's overall positive impact mechanism comprises three mediating effects: scaleoutput, factor complementarity, and innovation compensation. Financing constraints exert a negative moderating effect that weakens these three mediating pathways. 3. Due to the policy shock, enterprises increased demand for technical positions and showed greater preference for hiring highly educated and skilled personnel. 4. The policy exhibits verifiable spillover effects at the enterprise level: neighboring provinces experienced reduced employment and fewer employees in technology-intensive firms, with labor flowing from non-pilot to pilot regions.

Based on these findings, the following policy implications are proposed: 1. The carbon emissions trading market for the power generation sector has now been established nationwide. Efforts should continue to refine market rules and regulatory frameworks, extend carbon trading to small and medium-sized enterprises, and further boost corporate output and employment. 2. Government departments should refine the types and forms of environmental regulations currently in place. Drawing lessons from the carbon emissions trading pilot program, they should balance "mandatory" and "incentive-based" environmental regulations to achieve dual success in stabilizing employment and improving the environment. 3. Governments may implement incentive-based environmental regulations to drive corporate innovation and industrial upgrading, maximizing the employment-boosting effects of carbon credits. Authorities should respond to enterprises' needs during green innovation cycles, providing support to green innovation startups to create more green technology jobs and enhance production efficiency through technological advancement. 4. Contemporary society must prioritize talent development, focusing on cultivating highly skilled and highly educated labor. Local enterprises should align with national talent development strategies by offering relocation incentives to attract high-caliber professionals. Educational institutions must intensify retraining programs for mid-to-low-skilled workers, substantially enhancing vocational skills to prevent mass unemployment.

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