Carbon Markets in China: Strategic Interactions and Corporate Adaptation *

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Abstract

Examining seven regional Emission Trading System (ETS) and the national ETS in China, we explore the interplay between corporate behavior and carbon policies. We find that only firms expecting stringent carbon policies proactively reduce emissions, invest more in decarbonization technology, and observe carbon premium, but expectations of weaker policies lead to increased emissions. Cap-and-trade reduces both emission levels and intensity while tradable performance standards only reduce emission intensity. Carbon markets do not negatively affect corporate production. Our findings underscore the importance of strategic interactions between firms and governments in achieving effective carbon reduction outcomes.

Keywords: Carbon emissions, Carbon markets, Corporate behavior, Sustainable finance

JEL Codes: G31, G38, Q52, Q54, Q56

*We thank Thierry Foucault and Augustin Landier for very insightful comments. Zhanhui Chen acknowledges the financial support from the Hong Kong Research Grants Council (GRF 16504522 and GRF 16503423).

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1 Introduction

To mitigate global warming, governments have developed multiple strategies to incentivize firms to reduce carbon emissions and invest in low-carbon technologies. The Emissions Trading Scheme (ETS) is one of the most popular policies.[1] Numerous studies explore the design and effectiveness of the ETS (Fowlie et al., 2016; Cui et al., 2021, 2018; Martinsson et al., 2022). However, most of the studies only focus on the impact of ETS on firms' behavior and overlook the impact of firms' behavior on ETS policy designs. As the ETS markets are rapidly developing globally and policies evolve, ETS markets across countries are dynamically changing. On one hand, firms respond to the carbon policy changes by governments. On the other hand, governments adjust carbon policies, based on firms' responses. Therefore, when evaluating the effectiveness of ETS, it is essential to consider the strategic interaction between firms and governments.

For example, in areas where low-carbon technologies are underdeveloped, imposing stringent carbon emission policies is unrealistic and might lead to significant economic losses. Therefore, local governments often tailor their policy designs based on their observation of regional economic conditions and technological development. Similar to the government, firms can also observe regional economic conditions and use current information to predict future policy strictness. Therefore, firms are supposed to move based on their expectation of future policy using current information. This raises a question: If firms expect a weak carbon policy imposed by the local government, do they have incentives to strategically conceal their carbon-reduction technologies to compel the government to implement weaker carbon emission policies? Specifically, after the government announces future carbon emission policies, expecting a weak policy, might companies strategically increase their carbon emissions

[1]Emissions trading schemes (ETS) have become an increasingly popular policy instrument for climate change mitigation. ETS programs account for about 18% of global carbon emissions coverage in 2024 (World Bank, 2024). 20 active programs are operating in regions such as the European Union, New Zealand, China, South Korea, Kazakhstan, Switzerland, and 22 local areas including California and other states participating in the Regional Greenhouse Gas Initiative in the United States. Moreover, 15 additional programs are either planned or under consideration. The growing prevalence of ETS may facilitate the integration of national and regional climate policies, enhancing global mitigation efforts more efficiently.

and reduce investment in low-carbonization technologies? If so, the effectiveness of carbon emission policies would be greatly compromised. Therefore, understanding the strategic interactions between governments and firms can help us design better carbon emission policies.

This paper aims to answer these questions via examining various carbon emissions trading systems (ETS) in China. Carbon markets in China provide several unique features to help us understand the impacts of strategic interactions among governments, firms, and other stakeholders. First, there are seven regional carbon markets, which provide a unique panel of local governments and firms. These regional ETS are largely segmented, allowing for observing the interactions between local government policies and corporate choices. Second, high-quality data on carbon emission and green investment such as low-carbonization patents are available as firms are required to report actual carbon emissions in China. Our dataset allows us to observe the carbon emission data from 2007 to 2023, which covers both policy announcements (in 2011) and policy implementation (in 2013 and 2014). Third, China introduces the national ETS in 2021, which covers the power industry firms. Such institutional changes provide a unique window to observe the integration of regional carbon markets and exogenous changes in carbon policies.

We provide a comprehensive study of the impacts of carbon markets on firms in China. We investigate corporate behavior before the announcements of regional carbon markets, after the announcements, after implementing regional carbon markets, and after introducing the national ETS. Firms' expectations about carbon policies are critical for their corporate decisions. We first used information of local environmental policies to measure the strictness of local environmental policies before the announcements of pilot carbon markets in 2011. This provides an ex ante measure of local carbon policy for firms. We then test the impacts of the announcements or implementations of local carbon markets in regions expected to adopt weak, middle or strong policies. We find that after the announcements of regional carbon markets, firms in regions with weak or middle policies strategically increase carbon emission level and intensity, because they expect weak requirements imposed by the local governments and aim to gain some strategic advantage. In contrast, firms in regions with strong policies do not increase their emissions and do invest more in carbon-related technology and generate more patents, due to the expected tight carbon policies. As a result, stock markets react more strongly to carbon emissions for firms facing strong policies, after the announcements of local carbon markets. We also find that after the implementations, firms in regions with strong policies decrease carbon emission level and intensity and increase carbon-related patents, but not firms in weak regions, which is consistent with the announcement effects.

There are two often used carbon allowance policies, e.g., cap-and-trade (CT) and tradable performance standards (TPS), which are used in pilot carbon markets in China. One might wonder if carbon allowance policies matter. We find that firms under CT and in regions with strong policies decrease both emission levels and emission intensity, while firms under TPS and in regions with strong policies decrease emission intensity but increase the emission levels. As a result, stock markets respond more strongly to CT policies. Regarding the investment in decarbonization technology, we find firms in regions with strong carbon policies increase carbon-related patents, under either CT or TPS. That is, CT and TPS mainly differ in whether they target the emission level or intensity, and they are both effective in motivating firms to increase green investment.

Last, we study the introduction of the national ETS in 2021, which include all power industry firms with annual emissions exceeding 26,000 tons of CO_2. The national ETS market integrates regional carbon markets. Currently, the national ETS imposes less stringent requirements than those pilot regional markets, power industry firms previously covered in regional carbon markets face loosen carbon policies. We find that power industry firms in regions with weak carbon policies actually increase their emissions after transiting to the national ETS, while non-power firms in the same regions decrease their emissions. That is, local governments from those regions tighten carbon policies for non-power industry firms in order to meet the carbon reduction goal, e.g., suggesting the spill-over effect across industries and regions.

By considering the strategic interaction between firms and governments surrounding the carbon markets, our studies contribute to several strands of literature. Firstly, we contribute to the pollutant emission trading markets. Previous studies test the effectiveness of ETS without considering the announcement effects, firms' expectations, and the endogeneity of policy design (Bayer and Aklin, 2020; Cui et al., 2021). The most relevant paper to our studies is Biais and Landier (2022). Biais and Landier (2022) provide a theoretical model supporting our hypothesis. Biais and Landier (2022) show the strategic complementarity between government policies and corporate decisions. When firms expect tough carbon policies and hence invest more in green technology, governments will find imposing tougher carbon policies to be optimal. By contrast, if firms anticipate weak carbon policies and invest less in green technologies, then governments will find adopting weak carbon policies to be optimal. Due to the flexibility of regional policy design, China's regional ETS pilot program provides an ideal setting to test the model of Biais and Landier (2022). For example, our results reveal the strategic behavior of firms in regions with weak policies, i.e., increasing emissions following the announcements, which largely reduces the effectiveness of carbon policies.

Secondly, we contribute to the literature examining the pricing of carbon risks in various assets. The empirical evidence of carbon pricing is mixed. Numerous studies have found that carbon risks are priced in various assets, including stocks (Ferrell et al., 2016; Meng, 2017; Pedersen et al., 2021; Bolton and Kacperczyk, 2021, 2023), bonds (Huynh and Xia, 2021; Seltzer et al., 2022), and bank loans (Bartram et al., 2022; Ivanov et al., 2022), which suggest a carbon risk premium. Carbon risks also affect corporate policies (Shive and Forster, 2020; Antoniou et al., 2022) and institutional investors' holdings (Krueger et al., 2020; Cao et al., 2022; Liang et al., 2022). However, some studies show that low-carbon-intensity firms do not underperform or even outperform high-carbon-intensity firms in terms of stock returns or bond yields, contradicting the carbon premium hypothesis (Larcker and Watts, 2020; Chava, Kim, and Lee, 2021; Cheema-Fox, LaPerla, Serafeim, Turkington, and

Wang, 2021; Duan, Li, and Wen, 2023; Aswani, Raghunandan, and Rajgopal, 2024). The inconclusive evidence is mainly due to two limitations in prior studies. One is data quality and availability (Zhang, 2024). Another limitation is that prior studies examined carbon pricing from the perspective of a few (often one) market participants, without considering interactions among various market participants. When the carbon emission externality is not well controlled, corporate profit or market value maximization may not be optimal for shareholders, consumers, workers, and the public. Our studies contribute to the literature by using the true reported carbon emission data and by considering the strategic interaction between stakeholders.

The remainder of the paper is organized as follows. Section 2 provides background on carbon markets in China. Section 3 describes the data. Section 4 presents research design. Section 5 presents the main empirical results and Section 6 concludes.

2 Background: China's regional carbon markets

China's carbon emission trading markets have progressed through two stages: regional pilots and a national carbon emission trading system. The purpose of the regional pilot phase was to test different approaches to carbon trading under varying economic contexts, thereby facilitating the implementation of a nationwide carbon emission trading market. In October 2011, China's National Development and Reform Commission (NDRC) formally approved and announced seven regional carbon emission trading system (ETS) pilots, encompassing five cities (Beijing, Shanghai, Tianjin, Chongqing, and Shenzhen) and two provinces (Guangdong and Hubei). We will call these seven pilots as seven regions below. Later, Shenzhen, Beijing, Shanghai, Guangdong, and Tianjin launched their carbon emission trading markets in 2013, followed by Hubei and Chongqing in 2014. In 2021, the national carbon emission trading market for power sector was introduced. As of now, China's carbon emission markets have become the largest carbon trading markets globally. These pilot programs operated independently of one another. Different regions have discretionary power to decide the carbon allowance allocation policy and coverage, which we will discuss below.

2.1 Carbon allowance allocation policies

Different regions have different allowance allocation policies. Carbon allowance allocation policies can be broadly categorized into cap-and-trade (CT) and tradable performance standards (TPS).[2] Under a CT rule, a regulated firm's total allowance is determined before the compliance period, based on its historical emission levels. In contrast, under a TPS rule, the total allowance is based on a firm's production level at the end of each compliance period.

Under CT, allowance of firm i in year t in region k is given by

$$Allowance_{i,t} = HistoricalEmission \times \beta_{CT,k} \tag{1}$$

where $HistoricalEmission$ refers to the benchmark year for emission (e.g., past five-year historical emission) and $\beta_{CT,k}$ is the CT coefficient in region k.

Under TPS, allowance of firm i in year t in region k is given by

$$Allowance_{i,t} = Production_{i,t} \times \beta_{TPS,k} \tag{2}$$

where $Production$ refers to the output of firm i in year t and $\beta_{CT,k}$ is the TPS coefficient in region k.

Moreover, the coefficients $\beta_{CT,k}$ and $\beta_{TPS,k}$ capture the stringency of carbon allocation policy. For example, the smaller the coefficient (either $\beta_{CT,k}$ or $\beta_{TPs,k}$), the fewer allowances are allocated to firms, indicating a stricter policy in region k. Appendix B summarizes the carbon allocation policy in each region. It is important to note that the coefficients $\beta_{CT,k}$ and $\beta_{TPS,k}$ are not disclosed to firms before carbon trades in China.

[2] Our terminologies follow Burtraw et al. (2014), Goulder et al. (2019), Yeh et al. (2021), and Goulder et al. (2023). But some studies name CT and TPS as mass-based and rate-based, respectively.

2.2 Coverage

In addition to different carbon allocation policies, the pilot regions also varied in their coverage of firms in the regional ETS. For example, in Hubei Province, industrial firms with more than 40,000 tons of carbon emissions in either 2010 or 2011 were included in Hubei ETS. In contrast, Beijing ETS included firms with emissions of 10,000 tons or more. The lower the inclusion threshold, the more companies are mandated to participate in the regional carbon market, suggesting a more stringent carbon policy in the region.

2.3 Policy strictness

As regions have discretionary power to set up local carbon policies, it is important to compare policy strictness across regions. Also, carbon policies usually are not disclosed before ETS trades, firms have to choose carbon emission levels based on their expectations of carbon policies. After local ETS is implemented, firms understand the local carbon policies. Therefore, from the firm perspective, we employ ex-ante information set to predict future policy strictness before ETS starts and use ex-post policy disclosures once ETS starts.

2.3.1 Ex-ante information set

Our ex-ante information set contains three measures: firm-level environmental punishment, environmental investment by a local government, and third-party ratings. These three measures are based on the information available before the announcement of local carbon ETS.

First, we use the average air pollution fees and total pollution fees of publicly listed firms during 2009–2011 to proxy for firm-level environmental enforcement intensity. We see that Beijing, Shenzhen, Shanghai, and Guangdong charged higher air pollution fees and total pollution fees than Tianjin, Hubei, and Chongqing.[3] Therefore, we classify the first four regions (i.e., Beijing, Shenzhen, Shanghai, and Guangdong) as strong regions while the rest three regions as weak ones.

[3] See Appendix C for the details.

Second, we use the local government expenditure on environment protection over 2009–2011 to measure the environmental investment intensity of a local government.[4] We see that Guangdong, Beijing, Hubei and Shenzhen have higher environmental and pollution control budgets than Chongqing, Shanghai, and Tianjin. Therefore, we classify the first four regions (i.e., Guangdong, Beijing, Hubei, and Shenzhen) as strong regions while the rest three regions as weak ones.

Third, we use the City Green Development Index Rankings as the third-party ratings. The ratings are published by the Economic Climate Monitor Center of the National Bureau of Statistics of China in collaboration with Beijing Normal University and Southwestern University of Finance and Economics. This index considers the real air pollution change and other public reports. Among the 34 major and medium-sized cities participating in the assessment, the top ten cities in terms of green development levels are Shenzhen, Haikou, Kunming, Beijing, Hefei, Guangzhou, Dalian, Qingdao, Changsha, and Fuzhou and there are nineteen cities scored below the average level in green development. Therefore, we classify Beijing and Shenzhen as strong regions while the rest five regions as weak ones.

Table 1 summarizes these three ex ante measures in columns (1)–(3). A value of "1" indicates strict environmental policies. Column (4) provides summary classification. We classify a region as a strong one if it is strict in all columns (1)–(3), weak one if it is weak in all columns (1)–(3), and middle otherwise. We see that Beijing and Shenzhen have strong environmental policies, Chongqing and Tianjin have weak ones, while Shanghai, Guangdong, and Hubei are the middle ones.

2.3.2 Ex-post assessment

When regional ETS was launched, the local government issued detailed carbon policies to the public, including the coverage threshold and carbon allowance allocation policy. Therefore, we can cross check our classification of policy strictness which uses ex ante information.

[4]See Appendix D for the details.

Since local governments independently develop and operate their carbon markets, their carbon policies are usually different. Different regions may include different industries in local ETS, adopt different thresholds to includes firms in local ETS, use different allowance allocation policy (CT or TPS), or impose different CT or TPS coefficients. For example, the power industry employs cap-and-trade (CT) allocation in Chongqing but uses tradable performance standards (TPS) allocation in Beijing. Due to these differences in carbon policies, it is challenging to directly compare the policy strictness across regions. To address this difficulty, we consider both coverage thresholds and coefficients used in carbon allowance policies to construct measures at the region level.

First, we compare the coverage thresholds. For example, the coverage threshold in Tianjin is 20,000 tons of average carbon emission over 2009-2012. That is, firms in Tianjin with average carbon emissions higher than 20,000 tons will be included in the carbon market. Obviously, the lower the threshold, the more firms are included in the regional carbon markets, and the stricter the policy is. For this measure, we sort all regions based on their thresholds and classify a region as strong one if its threshold is below the median across all regions.

Next, we compare the coefficients used in carbon allowance policies TPS or CT. We compute the average CT (or TPS) coefficient for a region across all industries and then sort all regions based on the average CT (or TPS) coefficient. If a region employs a lower coefficient, the carbon emission allowance will be less, and hence the policy is stricter. Therefore, we classify a region as strong one if its coefficient is below the median across all regions.

Last, we summarize policy strictness from these three measures (including coverage threshold, CT coefficient, and TPS coefficient) for a region in Columns (1)–(3) of Table 2. We finally classify a region as a strong policy region if it is strong across all three measures. Similarly, a region will be considered a weak policy region only if it is weak across all three measures. Column (4) of Table 2 presents the results. We see that this ex post classification is consistent with the ex ante classification in Table 1.

3 Data

We collect plant-level emission and accounting data from China National Tax Survey Data (CNTSD) and merge it with several other datasets to construct a comprehensive database.

1. **China National Tax Survey Data (CNTSD)**: The database encompasses panel data at the plant level spanning from 2007 to 2016. It includes detailed accounting information such as the number of employees, annual total production output, total assets, total liabilities, and production equipment. Additionally, the database includes extensive environmental metrics. It includes the amount of coal, natural gas, and oil used; the amount of sulfur dioxide (SO2), nitrogen oxides (NOx), and wastewater produced; and the number of specialized environmental protection devices.

2. **China Industrial Enterprise Pollution Database**: The China Industrial Enterprise Pollution Database (1998–2014) supplements the environmental variables in the CNTSD by providing additional data on nitrogen oxide (NOx) emissions, sulfur dioxide (SO2) emissions, coal consumption, natural gas consumption, and other related environmental indicators.

3. **Chinese Industrial and Commercial Registered Enterprises Database**: The Chinese Industrial and Commercial Registered Enterprises Database adds to the CNTSD by providing supplementary information, including each enterprise's Unified Social Credit Identifier and precise geographic coordinates (latitude and longitude).

4. **China Stock Market & Accounting Research Database (CSMAR)**

   - **Carbon Emissions Trading Information Database**: The database provides daily trading data of regional carbon markets, including close prices, and trading volumes.

   - **Carbon Emission Market Company Information**: This dataset provides information on the companies participating in pilot carbon emission trading schemes on an annual basis. The treatment group in this paper is based on the firms identified in this database.

5. **Incopat Patent Database**: The database provides comprehensive patent information, including patent titles, abstracts, patent IDs, and other pertinent details.

6. **National Pollution Discharge Permits Administration Information Platform**: We manually collected firm-level carbon emissions data from the National Pollution Discharge Permits Administration Information Platform for all firms participating in the national ETS. Our dataset spans from 2019 to 2023, encompassing the pre-and post-implementation periods of the national carbon market

7. **The Emissions Database for Global Atmospheric Research**: Our city-industry level emissions data is sourced from EDGAR (the Emissions Database for Global Atmospheric Research), spanning from 1970 to 2023.

4 Empirical methodology

4.1 Difference-in-differences estimation

Our main identification is subgroup difference-in-difference (DiD) estimation (De Simone et al., 2024). Firms included in the pilot regional ETS are treated. We aim to study corporate behavior during three stages, i.e., before the announcements of pilot regional ETS, after the announcements but before implementing these regional ETS, and after implementing these regional ETS. We extend the standard DiD method to show heterogeneous effects on corporate behavior under different environmental policy strictness. We separate one treatment dummy into three treatment dummies, Strong, Middle, and Weak, denominating strong environmental policies, middle environmental policies, and weak environmental policies in a region, respectively. As discussed in Subsection 2.3, we use the ex ante (ex post) measure to classify these 7 regions before the announcements (implementation) of pilot ETS. The econometric specification for our DiD estimation is as follows:

$$y_{i,t} = \beta_1 Strong_i \times Post_t + \beta_2 Middle_i \times Post_t + \beta_3 Weak_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \quad (3)$$

where $y_{i,t}$ is the outcome variable of interests for firm i; $Strong_i$ $Middle_i$ $Weak_i$ are dummy variables that equal one if firm i is located in a region with strong, middle, or weak environmental policies, and zero otherwise; $Post_t$ is a dummy variable that equals one for the years when or after the treatment occurs and zero otherwise. We are interested in the impacts on carbon emission, carbon emission intensity, production, production equipment, labor, and the number of decarbonization-related patents. η_i represents firm-level fixed effects and σ_t represents year fixed effects. β_1, β_2, and β_3 show the average treatment effects of policy announcements on firms with different policy strictness.

4.2 Matched DiD estimation

The treated and untreated firms from pilot regions are not perfectly comparable, because only firms with high emissions are mandated in the pilot market, while firms with low emissions are not covered. Therefore, the emission level and firm size of the treatment group are usually larger than those of the untreated group. Although we could use between-region variations for identification, this would still lead to a biased result if firm significantly differ in their pre-treatment characteristics (Dehejia and Wahba, 2002). To address this concern, we follow Cicala (2015) and apply the propensity score matching (PSM).[5] Specifically, for each treated firm, we first find firms from the non-pilot neighborhood regions (usually, neighborhood provinces) and within the same sector. Then we consider their carbon emissions and firm production in 2009 and 2010 (two years before the policy announcement) and select 20

[5]Sepcifically, we apply the propensity score matching based Mahalanobis distance measure Kantor (2012).

untreated firms as the matched sample. Figure 1 shows the geographical distribution of treated firms and matched firms.

5 Results

Table 3 reports the summary statistics for the matched samples. All variables are in logarithm. Comparing the treated and untreated firms, we see that treated firms are larger (e.g., larger production, production equipment, and more labor employed), have higher carbon emission (in levels and intensity) and more carbon related patents.

5.1 Announcement effects

We first run panel regression of Equation (3) to examine the announcement effects of pilot regional ETS markets. That is, the treatment in Equation (3) is the announcement of starting a local ETS market. Since firms are unclear about the carbon policies around such announcements, we use the ex ante measure of environmental policy strictness to differentiate these seven pilot regions, e.g., Table 1.

Table 4 reports the regression results. First, compared with untreated firms, treated firms do not reduce their productions, as shown in Columns (3)–(5). In fact, we see their productions increase, especially for treated firms located in regions with middle or weak environmental policies. Second, Columns (1)–(2) show that treated firms located in regions with middle or weak environmental policies actually increase their carbon emissions, in both levels and emission intensity. This suggests that these firms intend to signal their carbon emission status, intending to gain some advantage during the implementation stage of local ETS later. Last, Column (6) shows that treated firms located in regions with strong environmental policies increase their carbon-related patents, suggesting these firms invest more in decarbonization technology.

Figure 2 compares the time series of carbon-related patents for treated firms in regions with strong and weak environmental policies. In this graph, we calculate the average number of patents related to decarbonization and subtract that of non-pilot regions. The model-free mean plot shows a clear pattern that firms expecting strong environmental policies will invest more in decarbonization technology.

For robustness check, we also perform a standard triple DiD test in Appendix E and Table E.12, comparing the announcement effects in regions with strong and non-strong (e.g., weak or middle) environmental policies. The results are qualitatively similar to those reported in Table 4. Again, we see that treated firms in regions with non-strong environmental policies strategically increase their carbon emissions after the announcements of pilot ETS while strong environmental policies induce firms to invest more in carbon-related technology.

Overall, the results suggest that a clear trend across policy strictness. We see that the announcements of pilot ETS do not negatively affect corporate production. If treated firms expect a weak policy, firms will tend to strategically increase their carbon emission without investing in decarbonization technology. On the other hand, treated firms from regions with strong environmental policies tend to invest more in decarbonization technology. Local governments also respond to such expectations in a consistent way. These results suggest the strategic interactions between firms and local governments.

5.2 Implementation effects

Next, we run panel regression of Equation (3) to examine the implementation effects of local ETS markets. That is, the treatment in Equation (3) is the implementation of a local ETS market. Since the carbon policies are disclosed to firms now, we use the ex post measure of carbon policy strictness to differentiate these seven pilot regions, e.g., Table 2.

Such classification of carbon policy strictness is confirmed by the carbon prices in these pilot ETS markets. Figure 3 plots the average annual carbon prices in ETS markets with strong or weak carbon policies. We compute the average annual carbon price in each market, weighted by daily trading volume or maximum trading volume. Consistent with our classification, Figure 3 shows that the average annual carbon prices of regions with strong carbon policies are consistently higher than those in regions with weak carbon policies.

Table 5 reports the panel regressions results from the matched sample. We see that both emission level (Column (1)) and emission intensity (Column (2)) decrease for treated firms located in regions with strong or middle carbon policies, but no impacts on firms in regions with weak carbon policies. Columns (3)–(5) show negligible impacts of pilot ETS on corporate production. The impacts on carbon-related patents are insignificant.

For robustness check, we also perform a standard triple DiD test in Appendix E. Table E.13 presents the implementation effects in regions with strong and non-strong (e.g., weak or middle) environmental policies. We see that treated firms in regions with strong environmental policies reduce their carbon emission levels and intensity, and invest more in carbon-related patents after implementing pilot ETS, which is similar to those reported in Table 5.

5.3 Comparing carbon allowance allocation policies: TPS vs. CT

One might wonder whether carbon allowance allocation policies matter. That is, if TPS or CT has different impacts on corporate behavior. We investigate this issue in this subsection.

One difficulty is that carbon allowance allocation policies (TPS or CT) may be endogenously chosen, given the strategic interaction between local governments and firms. That is, pilot regions endogenously chose TPS or CT for certain industries. We use instrumental variable to address this endogeneity issue. We observe that in order to implement TPS, local governments need to have information about firm production. However, such information may not be available to local governments in China due to several reasons. First, firms, especially non-listed firms, may not be required to disclosure their production information. Second, firms often have strong incentives of hiding their production information for the tax avoidance purpose. Therefore, the availability of production information is critical for local governments to decide whether use TPS or not. In practice, local governments rely on the reports from the National Bureau of Statistics of China to collect information about firm production. The National Bureau of Statistics of China requires enterprises above designated size to report their production. Over 2007-2010, the designated size was RMB 5 million. That means local governments have production information of a firm if its size is above RMB 5 million. This suggests that firms with a size above RMB 5 million are more applicable to TPS. Therefore, we use this threshold as an instrumental variable and run instrumental variable regressions. Taking treated firms under TPS as an example, the first-stage regression is:

$$TPS_{i,t} = \gamma_1 \mathbf{I}_{i,t,5m} + Controls_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $TPS_{i,t}$ is a dummy which equals one if firm i is treated under TPS in year t and zero otherwise; $\mathbf{I}_{i,t,5m}$ is a dummy which equals one if firm i has a size above RMB 5 million and zero otherwise; control variables ($Controls$) include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). After running the first-stage regression, we use the predicted TPS (e.g., $\widehat{TPS}_{i,t}$) to run the second-stage regression, as follows:

$$y_{i,t} = \beta_1 \widehat{TPS}_{i,t} \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{5}$$

where $y_{i,t}$ is the outcome variable of interests for firm i; $Post_t$ is a dummy variable that equals one for the years when or after the treatment occurs and zero otherwise; η_i represents firm-level fixed effects and σ_t represents year fixed effects. β_1 shows the average treatment effects of TPS on corporate behavior. We are interested in the impacts on carbon emission, carbon emission intensity, production, production equipment, labor, and the number of decarbonization-related patents. For firms under CT, we run similar instrumental variable regressions, e.g., replacing TPS in Equations (4) and (5) by CT.

Table 6 reports the results from the first-stage regression. To verify our choice of the instrumental variable, we consider various production thresholds, including RMB 5 million, RMB 10 million, RMB 15 million, RMB 20 million, RMB 25 million, and RMB 30 million. Indeed we see that only the threshold of RMB 5 million is statistically significant at the 1% level. This validates our instrumental variable.

Table 7 presents the second-stage regression results, examining the implementation effects of ETS with TPS allocation policies. Panel A shows that in regions with strong carbon policies, TPS increases the carbon emission level (in Column (1)) and production (in Column (3)) but reduces carbon emission intensity (in Column (2)). Carbon-related patents also increase in Column (6). However, Panels B anc C show that in regions with middle or weak carbon policies, carbon emission level or intensity does not change significantly under TPS.

Table 8 presents the second-stage regression results, examining the implementation effects of ETS with CT allocation policies. Panel A and B show that in regions with strong or middle carbon policies, CT reduces both carbon emission level (in Column (1)) and carbon emission intensity (in Column (2)), while there is no significant impacts in regions with weak carbon policy. Firms also increase carbon-related patents in regions with strong carbon policy.

Comparing results from Tables 7 and 8, we see that in regions with strict carbon policies, TPS helps to reduce carbon emission intensity but not emission levels while CT actually reduces both emission levels and intensity. More importantly, we see that the strictness of carbon policy policy matters a lot. It is necessary to impose strict carbon policy to reach the goal of reducing carbon emission and promoting carbon-related innovation.

5.4 Carbon premium

In this section, we examine how stock markets respond to regional carbon markets, with a particular focus on different carbon allowance allocation policies (CT or TPS) and policy strictness. Similar to (Zhang, 2024), we run the following regressions:

$$
\begin{aligned}
r_{i,t} &= \alpha + \beta\, Lagged\ Emission_{i,t} + \gamma Controls_{i,t} + \beta_2 \eta_i + \beta_3 \sigma_t, \\
r_{i,t} &= \alpha + \beta\, Lagged\ Emission\ Intensity_{i,t} + \gamma Controls_{i,t} + \beta_4 \eta_i + \beta_5 \sigma_t,
\end{aligned} \tag{6}
$$

where $r_{i,t}$ is the monthly return of firm i in month t; $Lagged\ Emission_{i,t}$ and $Lagged\ Emission\ Intensity_{i,t}$ are the natural logarithm of lagged carbon emission and emission intensity of company i ; $Controls_{i,t}$ include the firm's leverage ratio, book-to-market ratio, oil and gas exposure, market beta, and the natural logarithm of current-year production; η_i represents industry-level fixed effects and σ_t represents time fixed effects. We lag carbon emission level and intensity by 18 months to ensure the data is available to the markets (Zhang, 2024).

One empirical challenge is that a firm could have subsidiaries operating across different regions and thus subject to various carbon policies. To address this challenge, we aggregate the exposure of subsidiaries to regional carbon policies into the firm level, weighted by its contribution to the parent firm's total revenue. Specifically, we first assign a numeric value of 3 (2 or 1) to a region with strong (middle or weak) carbon policy, then we compute the revenue-weighted average policy exposure of firm i to policy strictness as follows:

$$
PolicyExposure_{i,t} = \sum^{j \in J} \frac{1}{Rev_{i,t}} (3 \times Strong_{j,t} \times Rev_{j,t} + 2 \times Middle_{j,t} \times Rev_{j,t} + Weak_{j,t} \times Rev_{j,t}), \tag{7}
$$

where $Strong_{j,t}$, $Middle_{j,t}$, $Weak_{j,t}$ are dummies which equal to one if subsidiary j of firm i is treated under strong policy, middle policy, weak policy in a region in year t, respectively; $Rev_{i,t}$ is the total revenue of parent company i in year t and $Rev_{j,t}$ is the revenue of subsidiary j in year t. Similarly, we compute firm i's exposure to CT (or TPS) policy as the revenue-weighted average:

$$
CTRatio_{i,t} = \sum^{j \in J} \frac{1}{R_{i,t}} (CT_{j,t} \times R_{j,t}), \tag{8}
$$

where $CT_{j,t}$ is a dummy variable which equals to one if subsidiary j is treated under CT policy in year t; $Rev_{i,t}$ is the total revenue of parent company i in year t and $Rev_{j,t}$ is the revenue of subsidiary j in year t. That is, $CTRatio_{i,t}$ measures the fraction of firm i's revenue exposed to CT policy. For firms' exposure to TPS, we can calculate a similar ratio $TPSRatio_{i,t}$, e.g., replacing TPS in Equations (8) by TPS.

We sort all listed companies into tercile portfolios, based on $PolicyExposure_{i,t}$ and categorize companies into three groups: Strong, Middle, and Weak. Then we run regressions of model (6) for the full sample or each group to examine stock market reactions to carbon emissions. Table 9 presents the regression results. Columns (1)–(3) show the regression results of carbon emission and Columns (4)–(6) show the regression results of carbon emission intensity. We consider three different periods, i.e., before the announcements of regional carbon markets (February 2007 – September 2010), after the announcements of regional carbon markets (October 2010 – May 2014), and after the implementation of regional carbon markets (June 2014 – February 2017). Panel A shows that stock prices negatively relate to carbon emission level and intensity after announcing pilot carbon markets, but no market reactions before the announcements, while there is some weak evidence in emission intensity after implementing regional carbon markets. Panels B-D further show that stock market reactions are mainly from regions with strong carbon policies. For example, Panel B shows that stock prices didn't respond to carbon emission in regions with weak policies.

Next, we investigate differential reactions of stock prices to carbon emissions under different allowance allocation policies. We categorize firms into three groups based on their $CTRatio_{i,t}$ and $TPSRatio_{i,t}$. A firm is classified as CT one if its $CTRatio_{i,t} > 0.3$ or TPS one if its $TPSRatio_{i,t} > 0.3$, and the rest are mixed firms. Table10 presents the regression results. The full-sample regressions in Panel A show that stock returns negatively relate to carbon emission after the announcement of pilot carbon markets, but there is no market reactions before the announcement, while there is some weak evidence in emission intensity after the implementation of regional markets. Panels B-D further show that most of market reactions come from CT policies.

5.5 The implementation effects of national ETS

In 2021, China launched its national carbon emissions trading scheme (ETS), covering all power industry firms with annual emissions exceeding 26,000 tons of CO_2. Power industry firms that previously operated under regional carbon markets were subsequently transferred to the national ETS regulatory framework from 2021 onward. Given the distinct regulatory approaches between the national ETS and regional carbon markets, this transition in regulatory oversight may induce heterogeneous effects on carbon emissions for firms in different regions and industries. For example, while power industry firms have been integrated into the national ETS, other carbon-intensive industries remain under regional market jurisdiction, including manufacturing, iron and steel production, and aviation industries. This regulatory bifurcation, where power sector firms transition to the national market while non-power industries maintain regional compliance obligations, potentially affects the carbon emission of non-power industries in the regional carbon markets.

To answer these questions, we examine the impact of the national ETS implementation on power industry firms in pilot regions (Beijing, Shanghai, Shenzhen, Guangdong, Hubei, Tianjin, and Chongqing) and spillover effects of national ETS on non-power industry in pilot regions, with emphasis on the heterogeneous effects across firms regulated under strong, middle, and weak regional carbon policies. We conduct the difference-in-difference method in the power industry using the following regression:

$$Emission_{i,t} = \beta_1 PilotRegion_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{9}$$

where $Emission_{i,t}$ is the logarithm carbon emission for firm i; $PilotRegion_i$ is a dummy variable that equals one if firm i is located in a pilot region, and zero otherwise; $Post_t$ is a dummy variable that equals one for the years when or after the treatment occurs and zero otherwise; η_i represents firm-level fixed effects and σ_t represents year fixed effects.

To investigate the heterogeneous effects of national ETS implementation across policy strictness, we apply the following regression model:

$$Emission_{i,t} = \beta_1 Strong_i \times Post_t + \beta_2 Middle_i \times Post_t + \beta_3 Weak_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{10}$$

where $Emission_{i,t}$ is the logarithm carbon emission for firm i; $Strong_i$, $Middle_i$, and $Weak_i$ are dummy variables that equal one if firm i is located in a region with strong, middle, or weak environmental policies, and zero otherwise; $Post_t$ is a dummy variable that equals one for the years when or after the treatment occurs and zero otherwise; η_i represents firm-level fixed effects and σ_t represents year fixed effects. β_1, β_2, and β_3 captures the average treatment effects of national carbon ETS implementation on firms with different policy strictness.

Table 11 presents the regression results for power industry firms in Panel A and non-power industry firms in Panel B. Column (1) shows that power industry firms in pilot regions significantly increase carbon emissions compared with power industry firms in non-pilot regions. Column (2) shows such increase is mainly driven by firms in pilot regions with weak policy strictness. In fact, the national ETS has lower regulatory stringency than all regional markets, as evidenced by its higher inclusion threshold. [6] Firms from regions with strong policies had previously invested in green innovation and therefore maintain their emission reduction trajectories despite transitioning to the more lenient national framework. Conversely, firms from weak regional markets, where they were not motivated to invest in green innovation, exhibit increased emissions upon joining the national ETS, given the lower emission regulation.

We further extend our analysis to examine the spillover effects of national ETS implementation on non-power sectors in Panel B. Employing the same empirical specification as in Equations (9) and (10), we study other carbon-intensive sectors, including manufacturing, iron and steel production, and aviation industries. Limited by data availability, we

[6] The threshold of the national market is 26,000 tons of CO_2 while the highest threshold in the regional markets is 20,000 tonnes of CO_2 emission in Chongqing

use city-by-industry level carbon emission data from the Emissions Database for Global Atmospheric Research (EDGAR) database. As such, we use region-fixed effects, instead of firm-fixed effects. Column (3) shows that the implementation of the national ETS in 2021 did not generate significant aggregate changes in carbon emissions in non-power industries. However, Column (4) reveals heterogeneous effects across regions: while there is no significant changes in carbon emissions in most pilot regions, regions with weak carbon policies exhibit a significant increase in emissions. This heterogeneous response can be attributed to a compensatory regulatory mechanism: as power sector firms in weak policy regions significantly increased their emissions following the transition to the national ETS, regional authorities strengthened their oversight of non-power sectors to maintain overall emission targets.

6 Conclusions

This paper provides a comprehensive study of the impacts of carbon markets in China. In particular, we depict the strategic interaction between firms and governments over the carbon policies over time, e.g., before the announcements of regional carbon markets, after the announcements, after the implementations, and after introducing the national ETS markets. We study corporate behavior (e.g., carbon emission levels and intensity, and carbon related patents) and stock market reactions surrounding the carbon markets.

Firms form their expectations about the strictness of local carbon policies based on the historical environmental policies. First, we find that after the announcements of regional carbon markets, firms in regions with weak or middle policies strategically increase carbon emission level and intensity as they foresee weak requirements imposed by the local governments, but firms in regions with strong policies increase carbon-related patents given the expected tight carbon policies. As a result, stock markets react to the announcements of local carbon markets for firms affected by strong policies. The implementation effects are consistent with the announcement effects. We find that after the implementations, firms in regions with strong policies decrease carbon emission level and intensity and increase carbon-related patents.

Second, we also compare different allowance allocation policies, e.g., CT and TPS. First, we find that firms under CT and in regions with strong policies decrease both emission levels and emission intensity, while firms under TPS and in regions with strong policies decrease emission intensity but increase the emission levels. As a result, stock markets respond more strongly to CT policies. Second, firms in regions with strong carbon policies increase carbon-related patents, under either CT or TPS.

Last, we study the introduction of the national ETS, which integrates regional carbon markets by covering all power industry firms. As the national ETS starts with less stringent requirements than those pilot regional markets, power industry firms in regions with weak carbon policies actually increase their emissions after transiting to the national ETS. To maintain the local carbon reduction goal, non-power firms in the same regions have to decrease their emissions, e.g., the spill-over effect to the non-power industries.

The strictness of carbon policies is critical to carbon reduction. These findings underscore the critical role of firms' strategic actions in shaping the effectiveness of environmental policies. The tendency of firms to manipulate emissions and innovation efforts in response to anticipated policy leniency highlights a feedback mechanism that can undermine policy objectives. Specifically, when firms reduce their low-carbon innovation and increase emissions to influence government decisions, policymakers may inadvertently set weaker policies based on observed regional capabilities, perpetuating a cycle of insufficient environmental action. Therefore, policymakers should consider implementing measures that mitigate firms' ability to influence policy through strategic manipulation, such as improving transparency and monitoring systems, and committing to predetermined policy pathways that are less susceptible to short-term firm behavior. By understanding and addressing the interactive dynamics between government policy design and firm responses, more effective carbon emission policies can be developed, ultimately contributing to better environmental outcomes and advancing global efforts to combat climate change.

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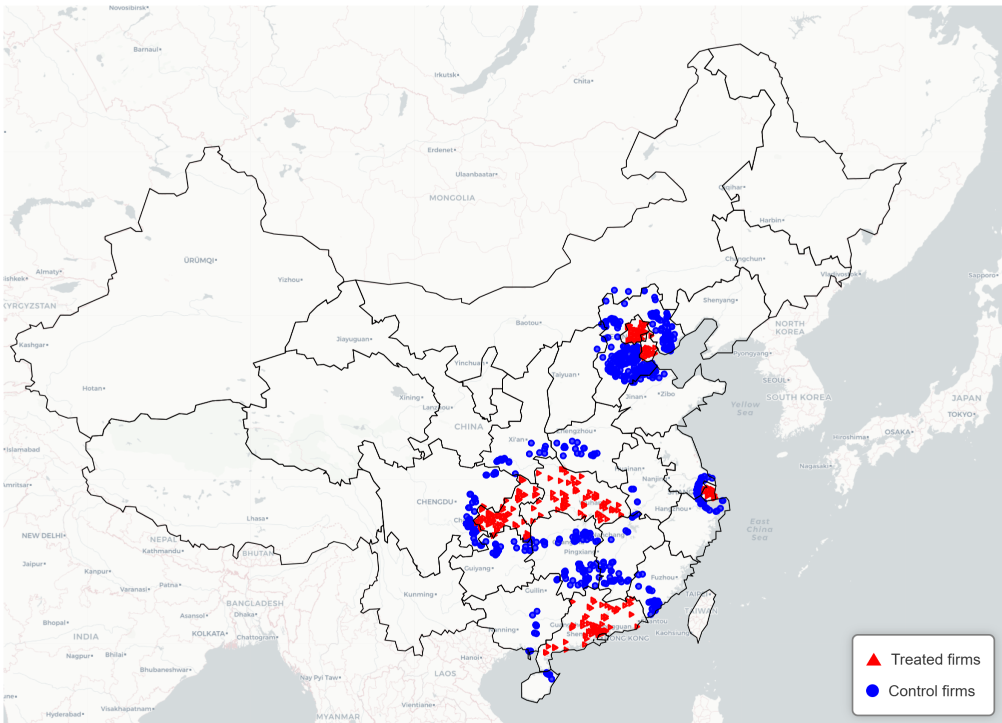

Figure 1: Geographical distribution of treated and matched firms

This figure presents the geographical distribution of treated firms (red dots) and matched firms (blue dots).

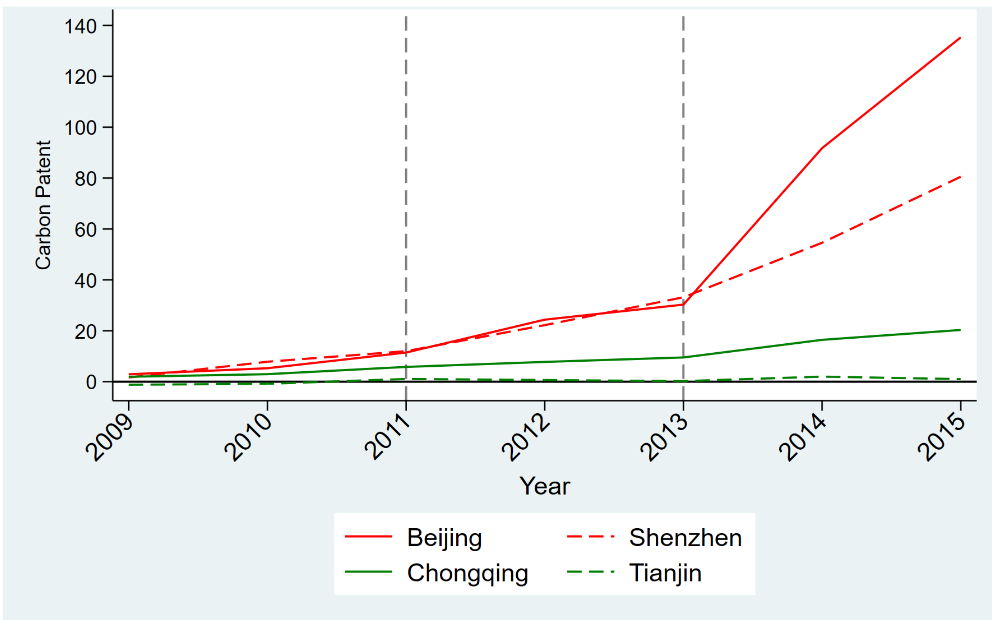

Figure 2: The average number of decarbonization-related patents

This figure plots the average number of patents related to decarbonization from firms with strong (the red lines, e.g., Beijing and Shenzhen) or weak (the green lines, e.g., Chongqing and Tianjin) environmental policies. We calculate the average number of patents related to decarbonization and subtract that of control groups from non-pilot regions.

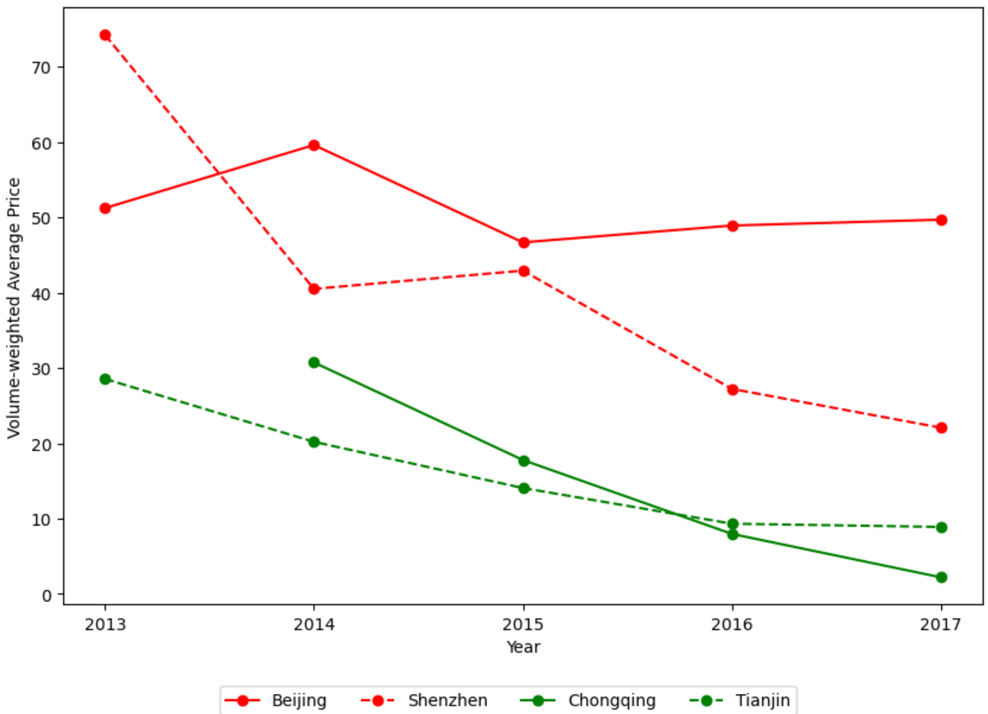

Figure 3: Average annual carbon prices

This figure presents the average annual carbon price in regions with strong carbon policies (red lines, e.g., Beijing and Shenzhen) and weak carbon policies (green lines, e.g., Chongqing and Tianjin). We use the daily trading volume as weights to compute the average carbon price in a year.

Table 1: Assessing environmental policy strictness using information before the announcements

This table summarizes whether a region adopts strict environmental policies before the announcements of pilot ETS, based on the pollution fees collected from public firms (in Column (1)), local government expenditure on environment protection (in Column (2)), and green city ratings (in Column (3)). A value of "1" indicates strict environmental policies. Column (4) provides summary classification, where a region has strong environmental policies if it is strict in Columns (1)-(3), weak environmental policies if it is weak in Columns (1)-(3), and middle otherwise. The sample period for pollution fees and the government environmental budget is from 2009 to 2011. The City Green ratings are for the year of 2011.

Region	Pollution fees (1)	Government environmental budget (2)	Green city rating (3)	Policy strictness (4)
Beijing	1	1	1	Strong
Shenzhen	1	1	1	Strong
Shanghai	1	0	0	Middle
Guangdong	1	1	0	Middle
Hubei	0	1	0	Middle
Chongqing	0	0	0	Weak
Tianjin	0	0	0	Weak

Table 2: Assessing carbon policy strictness based on the announced carbon policies

This table summarizes whether a region adopts strict carbon policies which were disclosed during implementing pilot ETS, based on the ETS coverage threshold (in Column (1)), the average CT coefficient (in Column (2)), and the average TPS coefficient (in Column (3)). A value of "1" indicates strict carbon policies. Column (4) provides summary classification, where a region has strong carbon policies if it is strict in columns (1)–(3), weak carbon policies if it is weak in Columns (1)–(3), and middle otherwise.

Region	Threshold (1)	CT coefficient (2)	TPS coefficient (3)	Policy strictness (4)
Beijing	1	1	1	Strong
Shenzhen	1	1	1	Strong
Shanghai	1	0	1	Middle
Guangdong	1	0	0	Middle
Hubei	0	1	0	Middle
Chongqing	0	0	0	Weak
Tianjin	0	0	0	Weak

Table 3:
Summary statistics

This table reports the summary statistics of treated and untreated firms, including their carbon emission, carbon emission intensity, production, production equipment, labor, and the number of carbon patents. Firms included in pilot regional ETS are treated ones. For each treated firm, we select 20 firms from untreated neighborhood regions in the same industry, with similar carbon emissions and production in 2010 and 2011, as matched firms. All numbers are in logarithmic values. The sample period is from 2007 to 2016.

	Untreated firms			Treated firms		
Variable	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.
Carbon emission	44,269	8.70	3.22	3,416	10.92	2.76
Carbon emission intensity	34,539	-2.51	2.74	2,411	-2.01	2.70
Production	48,875	10.89	2.30	4,540	12.45	1.93
Production equipment	59,602	9.55	2.74	6,050	11.38	2.33
Labor	62,357	4.97	1.75	6,179	6.28	1.52
Carbon patent	64,181	0.39	1.02	6,416	0.76	1.50

Table 4:
Announcement effects of regional ETS: DiD for regions with strong, middle, and weak environmental policies, using matched sample

This table examines the announcement effect of pilot regional ETS on corporate outcomes, using the difference in difference method over the period from 2009 to 2013. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, production equipment, labor number, and the number of carbon patents in Column (1)–(6), respectively. All dependent variables are in logarithm. The standard deviations of coefficient estimates are clustered at the industry level and reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). Two-way fixed effects are included (firm-fixed effects and year-fixed effects). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Production Equipment	(5) Labor	(6) Carbon Patent
Strong Policy	0.199*	0.134	0.0590	0.0632*	0.0840***	0.293***
	(0.0833)	(0.146)	(0.118)	(0.0279)	(0.0170)	(0.0740)
Middle Policy	0.469**	0.317*	0.0943	0.0829*	0.146***	0.0259
	(0.172)	(0.157)	(0.0496)	(0.0381)	(0.0399)	(0.0390)
Weak Policy	0.688***	0.360**	0.207*	0.0451	0.125***	0.0408
	(0.174)	(0.136)	(0.0905)	(0.0489)	(0.0256)	(0.0532)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	24168	17638	27585	33255	34245	34368

Table 5: Implementation effects of regional ETS: DiD for regions with strong, middle, and weak carbon policies

This table examines the implementation effects of pilot regional ETS on corporate outcomes, using the difference in difference method over the period from 2011 to 2016. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, production equipment, labor number, and the number of carbon patents in Column (1)–(6), respectively. All dependent variables are in logarithm. The standard deviations of coefficient estimates are clustered at the industry level and reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). Two-way fixed effects are included (firm-fixed effects and year-fixed effects). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Emission	Emission Intensity	Production	Production Equipment	Labor	Carbon Patent
Strong Policy	-0.802***	-0.636***	-0.122	0.0135	0.0197	0.157*
	(0.231)	(0.186)	(0.0866)	(0.0661)	(0.0376)	(0.0627)
Middle Policy	-0.706***	-0.936***	0.208**	0.143***	-0.0308	-0.00542
	(0.210)	(0.255)	(0.0766)	(0.0419)	(0.0466)	(0.0405)
Weak Policy	-0.0826	-0.0616	0.114*	0.0295	0.0955*	0.0237
	(0.175)	(0.169)	(0.0496)	(0.0315)	(0.0371)	(0.0464)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	68359	51301	67042	79032	79819	80261

Table 6: First-stage regression of TPS allocation policy

This table presents the first-stage regression results for the IV estimation. The dependent variable is a dummy which equals one if a firm is under TPS allocation policy and zero otherwise. The instrumental variable is a production threshold dummy. We consider various thresholds, including RMB 5 million, RMB 10 million, RMB 15 million, RMB 20 million, RMB 25 million, and RMB 30 million. The standard deviation of the coefficient estimate is reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). The sample period is from 2007 to 2010. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
5 million	0.174*					
	(0.0746)					
10 million		0.0939				
		(0.0712)				
15 million			0.0594			
			(0.0695)			
20 million				0.0261		
				(0.0680)		
25 million					-0.0195	
					(0.0664)	
30 million						-0.101
						(0.0650)
Other Controls	Y	Y	Y	Y	Y	Y
N	3830	3830	3830	3830	3830	3830

Table 7:
Implementation effects of TPS allocation policies: The second-stage regression

This table reports the second-stage regression results of the implementation effects of TPS allocation policy on corporate outcomes, using the difference in difference method over the period from 2011 to 2016. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, production equipment, labor number, and the number of carbon patents in Column (1)–(6), respectively. All dependent variables are in logarithm. Panels A, B and C present panel regression results from firms in regions with strong, middle, and weak carbon policies, respectively. The standard deviations of coefficient estimates are clustered at the industry level and reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). Two-way fixed effects are included (firm-fixed effects and year-fixed effects). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Production equipment	(5) Labor	(6) Carbon Patent
Panel A: Regions with strong carbon policies						
	0.169***	-0.373***	0.154***	-0.0529**	0.214***	0.313***
	(0.0380)	(0.0316)	(0.0276)	(0.0170)	(0.0217)	(0.0279)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	78655	59353	81564	96444	98097	98550
Panel B: Regions with middle carbon policies						
	-4.286	-2.361	0.247	0.392	-0.155	0.00982
	(2.825)	(3.428)	(0.138)	(0.343)	(0.192)	(0.283)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	78653	59348	81574	96474	98134	98588
Panel C: Regions with weak carbon policies						
	0.100	-0.0181	0.160***	0.0183	0.136*	-0.177***
	(0.162)	(0.146)	(0.0439)	(0.0771)	(0.0663)	(0.0531)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	78860	59442	81768	96703	98356	98809

Table 8:
Implementation effects of CT allocation policies: The second-stage regression

This table reports the second-stage regression results of the implementation effects of CT allocation policy on corporate outcomes, using the difference in difference method over the period from 2011 to 2016. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, production equipment, labor number, and the number of carbon patents in Column (1)–(6), respectively. All dependent variables are in logarithm. Panels A, B and C present panel regression results from firms in regions with strong, middle, and weak carbon policies, respectively. The standard deviations of coefficient estimates are clustered at the industry level and reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). Two-way fixed effects are included (firm-fixed effects and year-fixed effects). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Production equipment	(5) Labor	(6) Carbon Patent
Panel A: Regions with strong carbon policies						
	-0.770***	-0.688***	-0.0662	0.0293	0.0204	0.240**
	(0.204)	(0.204)	(0.0930)	(0.0646)	(0.0395)	(0.0743)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	79236	59739	82264	97232	98892	99346
Panel B: Regions with middle carbon policies						
	-0.749***	-0.830***	0.160	0.153***	0.00698	-0.00520
	(0.203)	(0.216)	(0.0845)	(0.0412)	(0.0441)	(0.0480)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	79349	59805	82675	98213	99890	100351
Panel C: Regions with weak carbon policies						
	-0.231	-0.0926	0.0828	0.0281	0.112*	0.113
	(0.183)	(0.186)	(0.0787)	(0.0529)	(0.0497)	(0.0753)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	79299	59753	82243	97258	98903	99368

Table 9: Carbon premium in regions with different policy strictness

This table reports the stock market reactions to carbon emission before the announcements of regional carbon markets (February 2007 – September 2010), after the announcements of regional carbon markets (October 2010 – May 2014), and after the implementation of regional carbon markets (June 2014 – February 2017), controlling for other firm characteristics. Columns (1) - (3) use carbon emission levels lagged 18 months, while Columns (4) - (6) use carbon emission intensity lagged 18 months. Panel A uses the full sample; Panel B (C or D) uses a subsample of firms facing weak (middle or strong) carbon policy. The standard deviations of coefficient estimates are reported in parentheses. Control variables include firms' leverage ratio, book-to-market ratio, oil and gas exposure, market beta, and the natural logarithm of current-year production. The regression includes time-fixed effects, industry-fixed effects and headquarter fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Feb 2007 – Sep 2010	Oct 2010 – May 2014	Jun 2014 – Feb 2017	Feb 2007 – Sep 2010	Oct 2010 – May 2014	Jun 2014 – Feb 2017
Panel A: Full Sample						
Emission	-0.00080	-0.00130***	0.00038			
	(0.001)	(0.000)	(0.001)			
Emission intensity				0.00631	-0.00889***	-0.01863*
				(0.006)	(0.003)	(0.011)
Panel B: Weak Policy						
Emission	0.00122	-0.00110	-0.00115			
	(0.003)	(0.001)	(0.004)			
Emission intensity				0.01535	-0.00401	-0.03618
				(0.036)	(0.007)	(0.024)
Panel C: Middle Policy						
Emission	-0.00063	-0.00101*	0.00016			
	(0.001)	(0.001)	(0.001)			
Emission intensity				0.00594	-0.00174	-0.00650
				(0.009)	(0.005)	(0.020)
Panel D: Strong Policy						
Emission	0.00041	-0.00355***	0.00085			
	(0.003)	(0.001)	(0.003)			
Emission intensity				-0.00003	-0.02300***	-0.21405***
				(0.012)	(0.008)	(0.079)
Time FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Headquarter FE	Y	Y	Y	Y	Y	Y

Table 10: Carbon premium in regions with different allowance allocation policies

This table reports the stock market reactions to carbon emission before the announcements of regional carbon markets (February 2007 – September 2010), after the announcements of regional carbon markets (October 2010 – May 2014), and after the implementation of regional carbon markets (June 2014 – February 2017), controlling for other firm characteristics. Columns (1) - (3) use carbon emission levels lagged 18 months, while Columns (4) - (6) use carbon emission intensity lagged 18 months. Panel A uses the full sample; Panel B (C or D) uses a subsample of firms facing CT (mixed or TPS) carbon policy. We categorize firms based on their exposure to CT policy ($CTRatio_{i,t}$) and TPS policy ($TPSRatio_{i,t}$). A firm is classified as CT one if its $CTRatio_{i,t} > 0.3$ or TPS one if its $TPSRatio_{i,t} > 0.3$, and the rest are mixed firms. The standard deviations of coefficient estimates are reported in parentheses. Control variables include firms' leverage ratio, book-to-market ratio oil and gas exposure, market beta, and the natural logarithm of current-year production. The regression includes time-fixed effects, industry-fixed effects and headquarter fixed effects. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Feb 2007 – Sep 2010	Oct 2010 – May 2014	Jun 2014 – Feb 2017	Feb 2007 – Sep 2010	Oct 2010 – May 2014	Jun 2014 – Feb 2017
Panel A: Full Sample						
Emission	-0.00080	-0.00130***	0.00038			
	(0.001)	(0.000)	(0.001)			
Emission intensity				0.00631	-0.00889***	-0.01863*
				(0.006)	(0.003)	(0.011)
Panel B: Cap & trade policy						
Emission	0.00015	-0.00173*	0.00077			
	(0.002)	(0.001)	(0.002)			
Emission intensity				0.00990	-0.01093**	-0.14849**
				(0.012)	(0.005)	(0.067)
Panel C: Mixed policy						
Emission	0.00013	-0.00150***	0.00045			
	(0.001)	(0.001)	(0.002)			
Emission intensity				0.00993	-0.00551	-0.00530
				(0.011)	(0.005)	(0.015)
Panel D: Tradable performance standard policy						
Emission	-0.01423	-0.00381	0.00766			
	(0.010)	(0.003)	(0.007)			
Emission intensity				0.00012	-0.01258	0.05245
				(0.020)	(0.038)	(0.063)
Time FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Headquarter FE	Y	Y	Y	Y	Y	Y

Table 11: Implementation effects of national ETS on firms in the pilot regions

This table examines the impact of national carbon market implementation on firms in pilot regions (Beijing, Shanghai, Shenzhen, Guangzhou, Chongqing, and Tianjin), using the difference in difference method. The independent variable is the natural logarithm of firm's carbon emission. Panel A compares power industry firms in pilot regions and non-pilot regions while Panel B compares aggregate non-power industry firms in pilot regions and non-pilot regions. Columns (1) and (3) present the baseline regression results for the full sample. Columns (2) and (4) present the heterogeneous effects across regions with different policy strictness (strong, middle, and weak). Two-way fixed effects are included (firm or region-fixed effects and year-fixed effects. The sample period is from 2019 to 2023. Standard errors are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Power firms		Panel B: Non-power firms	
	(1)	(2)	(3)	(4)
	Full sample	By policy strictness	Full sample	By policy strictness
Treatment × Post	0.112***		-0.014	
	(0.0363)		(0.0127)	
Strong Region × Post		0.210		-0.025
		(0.1359)		(0.0216)
Middle Region × Post		0.068		0.017
		(0.0413)		(0.0179)
Weak Region × Post		0.270***		-0.048**
		(0.0858)		(0.0216)
Firm FE	Y	Y		
Region FE			Y	Y
Time FE	Y	Y	Y	Y

Appendix

A Variable Definitions, Data Sources, and Sample Period

Carbon emission Carbon emission includes both direct and indirect emissions. Direct carbon emission comes from the combustion of fossil fuels such as gas, oil, coal, etc. Indirect carbon emission comes from the consumption of purchased electricity or heat. For each firm, the direct carbon emission is calculated by multiplying the consumption of each energy type by its carbon emission factor, which is summarized in Table A.1.

Table A.1: China's CO_2 Emission Factors

Energy Type	Unit	Emission Factor
Panel A: Emission Factors of Coal, Oil and Natural Gas		
Coal	$kgCO_2/kg$	1.978
Oil	$kgCO_2/kg$	3.065
Natural Gas	$kgCO_2/m^3$	1.809
Panel B: Emission Factors of Electricity		
North China Grid	$kgCO_2/kWh$	0.8843
Northeast China Grid	$kgCO_2/kWh$	0.7769
East China Grid	$kgCO_2/kWh$	0.7035
Central China Grid	$kgCO_2/kWh$	0.5257
Northwest China Grid	$kgCO_2/kWh$	0.6671
China Southern Power Grid	$kgCO_2/kWh$	0.5271

Note: China's electricity network is divided into six regional grids and each grid has its own carbon emission factor. The North China Grid includes Beijing, Tianjin, Hebei, Shandong, Shanxi, and Inner Mongolia. The Northeast China Grid covers Liaoning, Jilin, and Heilongjiang. The East China Grid encompasses Shanghai, Jiangsu, Zhejiang, Anhui, and Fujian. The Central China Grid consists of Henan, Hubei, Hunan, Jiangxi, Chongqing, and Sichuan. The Northwest China Grid spans Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The China Southern Power Grid manages Guangdong, Guangxi, Yunnan, Guizhou, and Hainan.
Source of Panel A: Department of Energy Statistics, National Bureau of Statistics of China and IPCC Guidelines for National Greenhouse Gas Inventories.
Source of Panel B: National Center for Climate Change Strategy and International Cooperation, National Development and Reform Commission of China.

The calculation methodology aligns with China's Emissions Trading Scheme (ETS). Energy and electricity consumption data are primarily sourced from China National Tax Survey Data (CNTSD), supplemented by the China Enterprise Pollution Emission Database. Carbon emissions are measured in logarithmic tons. The sample period is from 2007 to 2016.

Production Production is measured by the total industrial output value, defined as the aggregate monetary value of products and services generated by industrial enterprises during a calendar year. The production data are obtained from the CNTSD and expressed in logarithmic thousands of RMB. The sample period is from 2007 to 2016.

Carbon emission intensity Carbon emission intensity is calculated as the ratio of carbon emissions to firm output, expressed in logarithmic tons per thousand RMB. Specifically, carbon emission intensity equals to carbon emission divided by production. The sample period is from 2007 to 2016.

Labor Labor is measured as the total number of employees, expressed in logarithmic values. The data are sourced from CNTSD and the sample period is 2007 to 2016.

Production Equipment Production equipment is proxied by specialized production machinery and equipment investments, derived from CNTSD. Specifically, the measurement utilizes tax exemptions, which constitute 10% of the acquisition value of specialized production equipment in a given fiscal year. The values are expressed in logarithmic thousands of RMB, and the sample period is 2007-2016.

Carbon Patent Carbon patents are constructed using the Incopat Patent Database, which provides patent information including titles, abstracts, and International Patent Classification (IPC) ID at the firm-year level. To identify low-carbon technology patents, we employ the classification criteria outlined in China's Green Technology Patent Classification System.[7] China's Green Technology Patent Classification System provides a guideline to identify low-carbon patents based on IPC. Specifically, we extract patents from the Incopat Patent Database related to low-carbon technologies based on their IPC and express the count in logarithmic values. The sample period is from 2007 to 2016.

Company address Company addresses are obtained from the Industrial Enterprise Registration Database and converted into geographical coordinates (latitude and longitude). These spatial identifiers are employed as one of the matching variables in our empirical analysis. The sample period is 2007-2016.

Treatment The information of treated firms in each pilot is primarily sourced from the China Stock Market & Accounting Research Database (CSMAR) database, which provides the company name, unified Social Credit Identifier, industry code, etc. The sample period is 2013-2021.

Pollution fees The pollution discharge fee data and their corresponding regulatory standards are extracted from the annual China Statistical Yearbooks. The data collection encompasses the period of 2009-2011.

Carbon Price Carbon price data are extracted from the CSMAR database, which provides daily trading information for carbon emission allowances across all pilot ETS. The dataset encompasses detailed market indicators including close prices, open prices, daily price ranges (high and low), and trading volumes. The sample period is from 2013 to 2016.

B Carbon allowance allocation policy

The allowance allocation policy of each pilot region is manually collected from the official website of local government, which was disclosed after the launch of carbon markets. The

[7] The patent classification system is available at `https://www.gov.cn/zhengce/zhengceku/202308/P020230831576368049075.pdf`.

allocation policy includes allocation coefficients (CT coefficients and TPS coefficients), regulated industry, coverage threshold, carbon emission measurement methodology, etc. The following table summarizes the detailed allocation policy for each industry in seven pilot regions every year.

Table B.2: Allocation Policy in Shanghai

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2015	Steel Industry, Petrochemical Industry, Chemical Industry, Nonferrous Metals Industry, Building Materials Industry, Textile Industry, Paper Industry, Rubber Industry, Chemical Fiber Industry, Retail Industry, Hospitality Industry, Commercial Real Estate, Aviation Industry		Electric Power Industry, Aviation Industry, Port Industry, Airport Industry
2016-2017		Aviation, Port, Water Transportation, Tap Water Production, Industrial Enterprise	Electric Power, Thermal Power, Automotive Glass Production
2018-2022	Shopping Mall, Hotel, Commercial Office, Airport Terminal	Industrial Enterprise, Aviation Enterprise, Port Enterprise, Water Transport Enterprise, Tap Water Production Enterprise	Electric Power, Thermal Power

Table B.3: Allocation Policy in Beijing

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2015	Manufacturing, other industrial and service enterprises (units)	Heating enterprises (units) and thermal power generation enterprises	Power Generation, Electric Grid, District Heating, Data Center Operations
2016	Petrochemical, cement, manufacturing and other industries, other service industries, transportation industry enterprises	Mobile emission facilities of heating enterprises (units) and thermal power generation enterprises, gas and water production and supply enterprises, and transportation enterprises	
2017-2019		Heating enterprises (units), gas and water production and supply enterprises	Power generation enterprises (combined heat and power)
2020-2021	Cement, petrochemicals, other services, other industries (except electricity supply, water production and supply and other power generation industries)	Thermal power production and supply industry, electricity supply among other industries, water	Thermal power generation industry (combined heat and power)
2022		Production and supply of water to other industries	Thermal power generation industry (combined heat and power), cement manufacturing industry, heat production and supply, other power generation and power supply industries, key data center units

Table B.4: Allocation Policy in Tianjin

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2018	Steel, chemicals, petrochemicals, oil and gas extraction		Electricity and heat industry (including power generation, combined heat and power, heating, and power supply enterprises)
2019-2020	Steel, chemical industry, petrochemical, oil and gas extraction, aviation industry	Electricity and heat industry (including power generation, combined heat and power, heating, and power supply enterprises), building materials industry, and paper industry enterprises	
2021	Enterprises in the steel, chemical, petrochemical, oil and gas mining, aviation, non-ferrous metals, mining, food and beverage, pharmaceutical manufacturing, agricultural and sideline food processing, machinery and equipment manufacturing, and electronic equipment manufacturing industries	Building materials and paper industry companies	
2022-2023	Steel, chemical industry, petrochemical, oil and gas exploration, aviation, non-ferrous metals, machinery and	Building materials industry	

Table B.5: Allocation Policy in Guangdong

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2014	Cogeneration units in the power industry, comprehensive resource utilization generator units (using fuels such as coal gangue, oil shale, etc.), mining, micro powder grinding and special cement (white cement, etc.)		Coal-fired and gas-fired pure generating units in the electric power industry, ordinary cement clinker production and grinding in the cement industry, and long-process enterprises in the steel industry
2015-2016	Gas-fired cogeneration units and comprehensive resource utilization generator units in the electric power industry (using coal gangue, oil shale and other fuels), mining, micro powder grinding and special cement production		Coal-fired and gas-fired pure generating units and coal-fired combined heat and power units in the power industry, cement ordinary clinker production and grinding in the industry, and long-process enterprises in the steel industry
2017-2018	Mining in the cement industry, micro-powder grinding production, short-process enterprises in the steel industry and other steel enterprises, and enterprises in the petrochemical industry	Comprehensive utilization of resources in the power industry: power generation units and heating boilers, special paper making and paper product manufacturing enterprises	Coal-fired and gas-fired generating units in the power industry (including heating and cogeneration units), water clinker production and grinding, long-process enterprises in the steel industry, general papermaking and product manufacturing companies
2019-2021	Mining in the cement industry, steel rolling and processing processes in the steel industry, and enterprises in the petrochemical industry	The power industry uses special fuel generator sets and heating boilers, other grinding products in the cement industry	Coal-fired and gas-fired generating units (including combined heat and power units), cement industry clinker production and grinding, coking, lime burning, pelletizing, sintering
2022	Mining and petrochemical industry enterprises in the cement industry (except coal hydrogen production equipment)		
2023	Enterprises in the mining and petrochemical industries (except coal-based hydrogen production units), and textile industry (voluntary inclusion)	Other grinding products, steel rolling processes, outsourced fuel blending, chemical pulp manufacturing, ceramics, transportation industry	Clinker production and cement grinding, coking, lime burning, pelletizing, sintering, ironmaking, papermaking, and data center enterprises

Table B.6: Allocation Policy in Shenzhen

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2019	Others		Electricity, gas and water supply companies
2020		Others	Power supply, water supply, gas supply, buses, subways, hazardous waste treatment, sludge treatment, sewage treatment, ports and terminals, manufacturing and other industries
2021-2022		Buses, subways, hazardous waste treatment, sludge treatment, sewage treatment, ports and terminals, manufacturing and other industries	Electricity, water supply, gas supply
2023	Hotels, supermarkets and other service industries and universities		

Table B.7: Allocation Policy in Hubei 2013-2016)

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2014	Glass and other building materials, textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, ceramic manufacturing, medicine, non-ferrous metals and other metal products, paper making, cement, heating, combined heat and power		Power Industry
2015	Glass and other building materials, textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, ceramic manufacturing, medicine, non-ferrous metals and other metal products, paper making		Cement, power, heating, combined heat and power
2016	Textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, medicine, non-ferrous metals and other metal products, paper making		Cement, power, heating, combined heat and power

Table B.8: Allocation Policy in Hubei (2017-2020)

Year	Historical base (mass)	Historical base (rate)	Performance-based
2017	Textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, medicine, nonferrous metals and other metal products	Glass and other building materials, ceramic manufacturing, paper making	Cement, power, heating, combined heat and power
2018	Textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, medicine, nonferrous metals and other metal products	Glass and other building materials, ceramic manufacturing, paper making, heating, combined heat and power	Cement, power
2019	Textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, medicine, nonferrous metals and other metal products	Glass and other building materials, ceramic manufacturing, paper making, heating, combined heat and power, water production and supply, equipment manufacturing	Cement, power
2020	Textile industry, steel, chemical industry, automobile manufacturing, equipment manufacturing, petrochemical, food and beverage, medicine, nonferrous metals and other metal products	Power, glass and other building materials, ceramic manufacturing, paper making, heating, combined heat and power, water production and supply, equipment manufacturing	Cement

Table B.9: Allocation Policy in Chongqing

Year	Historical base (mass)	Historical base (rate)	Performance-based
2013-2020	All		

C Pollution fees

Table C.10: Air pollution fees and total pollution fees

This table reports the average air pollution fees and the average total pollution fees charged for listed companies headquartered within a pilot region. The sample period is 2009-2011.

Region	Average air pollution fees	Region	Average total pollution fees
Chongqing	326,413.87	Chongqing	924,666.12
Hubei	396,708.60	Hubei	1,124,198.10
Tianjin	550,318.12	Tianjin	1,586,295.20
Guangdong	595,307.97	Guangdong	1,698,210.90
Shenzhen	624,792.68	Shenzhen	1,799,616.50
Shanghai	930,563.22	Shanghai	2,660,508.90
Beijing	4,915,939.20	Beijing	14,121,698.00

D Government Expenditure on Environment Protection

Table D.11: Government expenditure on environment protection

This table reports the average local government expenditure on environment protection in a region (in RMB 100 Million). The data are sourced from the National Bureau of Statistics of China. The sample period is 2009-2011.

Province	Budget
Tianjin	27.37
Shanghai	47.42
Chongqing	59.52
Hubei	64.01
Beijing	69.80
Shenzhen	73.26
Guangdong	292.03

E Robustness Check: Triple DiD

In this subsection, we perform a standard triple DiD to examine the announcement or implementation effects of pilot ETS on corporate behavior, as follows:

$$y_{i,t} = \beta_1 Treatment_i \times Post_t + \beta_2 Treatment_i \times Post_t \times Strong_i + \beta_3 \eta_i + \beta_4 \sigma_t + \epsilon_{i,t}, \quad (11)$$

where $y_{i,t}$ is the outcome variable of interests for firm i; $Treatment_i$ is a dummy variable that equals one if firm i is enrolled in the pilot ETS, and zero otherwise; $Strong_i$ is a dummy variable that equals one if firm i is located in a region with strong environmental policies and zero otherwise (e.g., regions with weak or middle environmental policies); $Post_t$ is a dummy variable that equals one for the years when or after the treatment occurs and zero otherwise. We are interested in the impacts on carbon emission, carbon emission intensity, production, production equipment, labor, and the number of decarbonization-related patents. η_i represents firm-level fixed effects and σ_t represents year fixed effects.

Table E.12 reports the panel regression results of announcement. The significantly positive coefficients of the interaction term of $Post$ and $Treatment$ (e.g., Post X Treatment) in Column (1) and (2) indicate firms in regions with weak or middle environmental policies strategically increased their carbon emission level and intensity after the policy announcements by increasing their production, which is evidenced by the positive coefficients of $Production$, $Production\ Equipment$, and $Labor$. The significantly negative coefficients for the triple interaction term (e.g., Post X Treatment X Strong) in carbon emission and emission intensity indicates that firms in regions with strong environmental policies decreased their carbon emission. In addition, Column (6) shows that these firms increase their investment in low-carbon technology.

Table E.12:
Announcement effects of regional ETS: DiDiD for regions with strong and non-strong environmental policies

This table examines the announcement effect of pilot regional ETS on corporate outcomes, using the DiDiD method over the period from 2009 to 2013. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, production equipment, labor number, and the number of carbon patents in Column (1)–(6), respectively. All dependent variables are in logarithm. The standard deviations of coefficient estimates are clustered at the industry level and reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). Two-way fixed effects are included (firm-fixed effects and year-fixed effects). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Production Equipment	(5) Labor	(6) Carbon Patent
Post X Treatment	1.270***	1.087***	0.148*	0.138**	0.102**	-0.0277
	(0.213)	(0.228)	(0.0681)	(0.0488)	(0.0357)	(0.0295)
Post X Treatment X Strong	-0.775*	-0.785*	-0.0475	-0.108	-0.0199	0.274***
	(0.300)	(0.364)	(0.152)	(0.0709)	(0.0592)	(0.0817)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	23495	17590	26218	31409	32282	32417

Table E.13:
Implementation effects of regional ETS: DiDiD for regions with strong and non-strong environmental policies

This table examines the implementation effect of pilot regional ETS on corporate outcomes, using the DiDiD method over the period from 2011 to 2016. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, production equipment, labor number, and the number of carbon patents in Column (1)–(6), respectively. All dependent variables are in logarithm. The standard deviations of coefficient estimates are clustered at the industry level and reported in parentheses. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). Two-way fixed effects are included (firm-fixed effects and year-fixed effects). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Emission	Emission Intensity	Production	Production Equipment	Labor	Carbon Patent
Post X Treatment	0.0736	-0.00281	-0.0361	-0.0608	0.104*	-0.0102
	(0.139)	(0.145)	(0.0713)	(0.0526)	(0.0446)	(0.0305)
Post X Treatment X Strong	-0.525*	-0.591**	0.0677	0.0870	-0.141*	0.172***
	(0.220)	(0.227)	(0.109)	(0.0803)	(0.0679)	(0.0465)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	73998	53852	58627	73533	74608	74662

F Parallel trend test

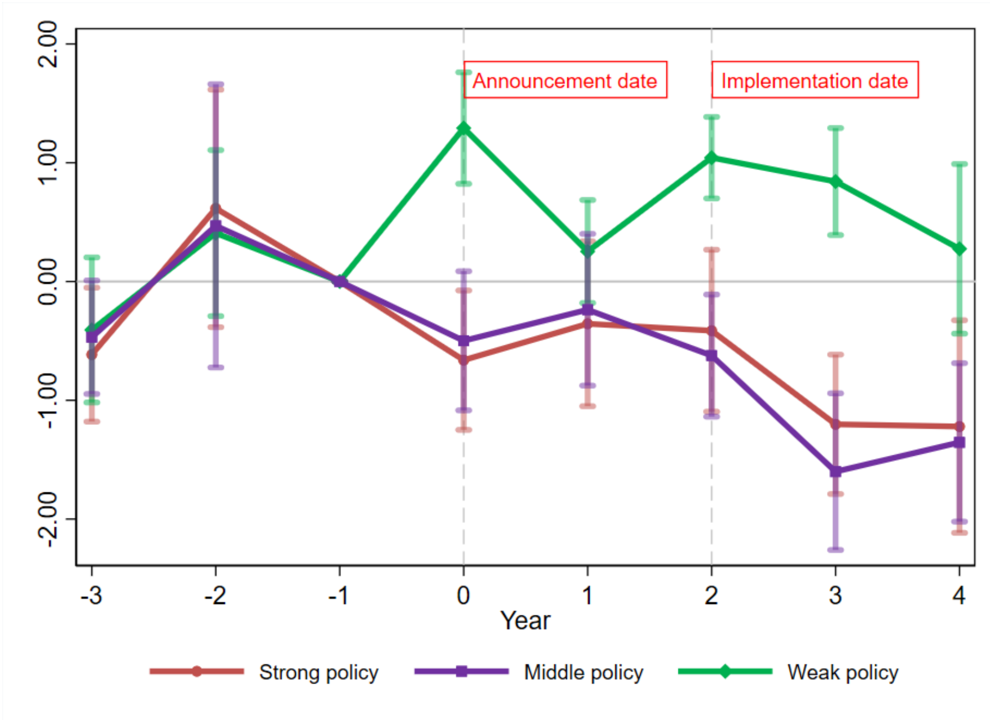

Figure 4: Parallel trend test for carbon emission

This figure presents the parallel trend test of carbon emissions in regions with strong (red line), middle (purple line), and weak (green line) environmental policies. The two vertical gray dashed lines indicate the announcement date (at year 0) and the implementation date (at year 2), respectively.

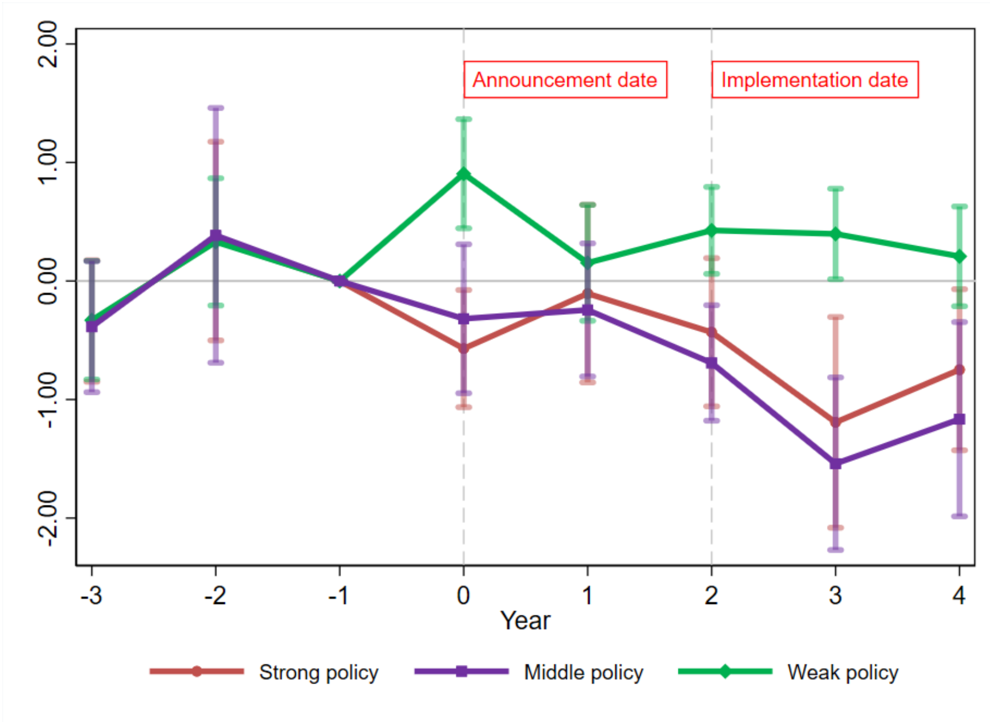

Figure 5: Parallel trend test for carbon emission intensity

This figure presents the parallel trend test of carbon emission intensity in regions with strong (red line), middle (purple line), and weak (green line) environmental policies. The two vertical gray dashed lines indicate the announcement date (at year 0) and the implementation date (at year 2), respectively.

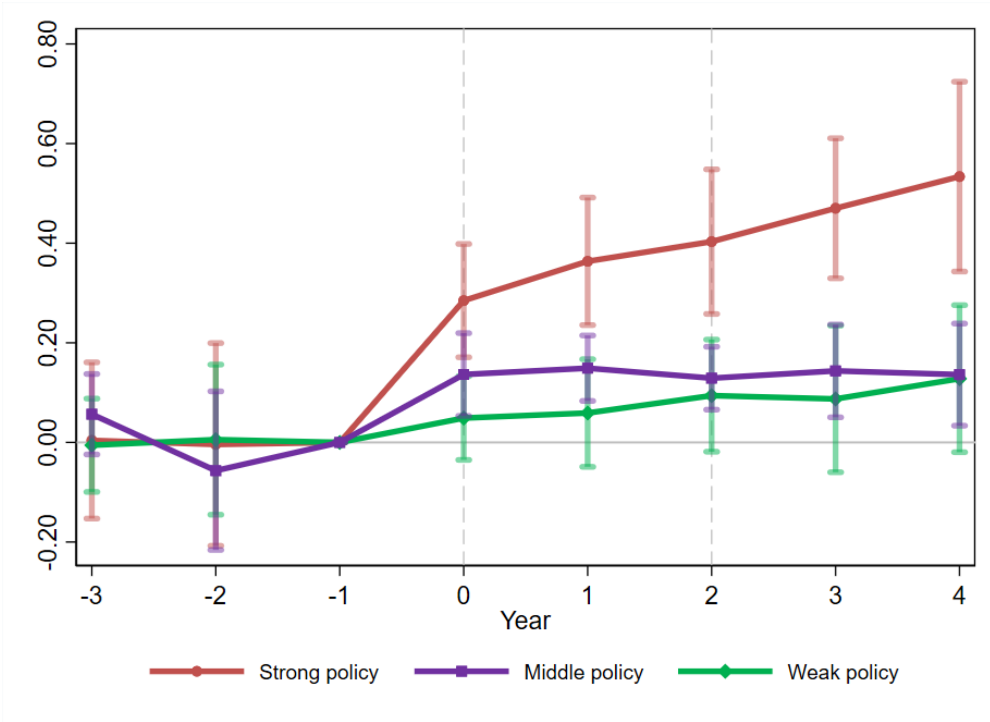

Figure 6: Parallel trend test for the number of carbon-related patents

This figure presents the parallel trend test of the number of carbon-related patents in regions with strong (red line), middle (purple line), and weak (green line) environmental policies. The two vertical gray dashed lines indicate the announcement date (at year 0) and the implementation date (at year 2), respectively.

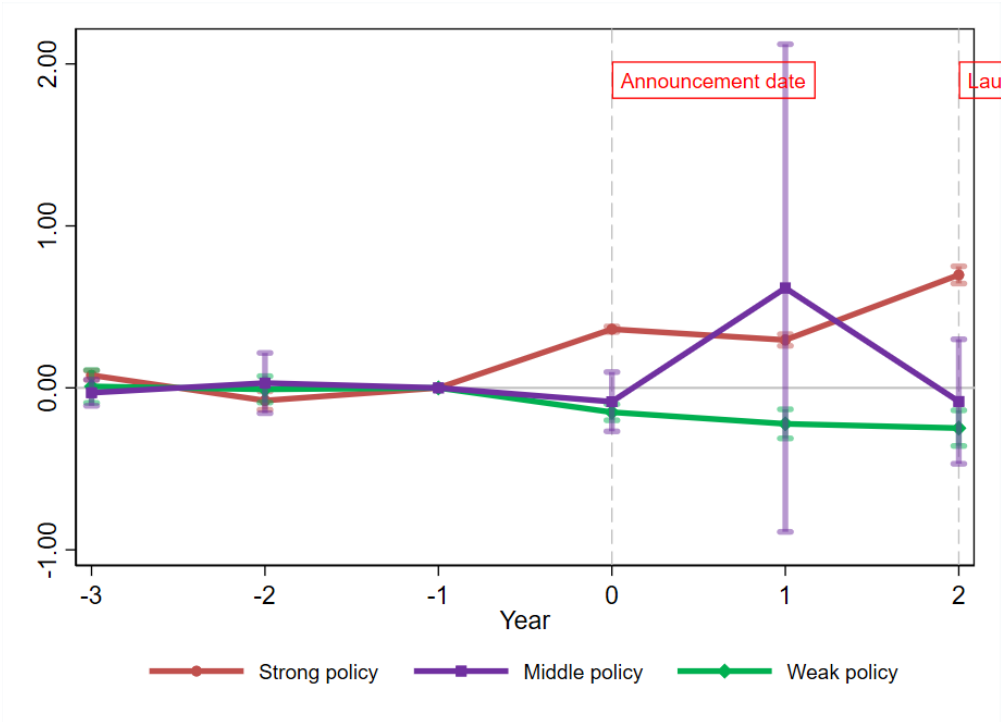

Figure 7: Parallel trend test for the number of carbon-related patents under TPS policies

This figure presents the parallel trend test of the number of carbon-related patents in regions with strong (red line), middle (purple line), and weak (green line) TPS policies. The two vertical gray dashed lines indicate the announcement date (at year 0) and the implementation date (at year 2), respectively.

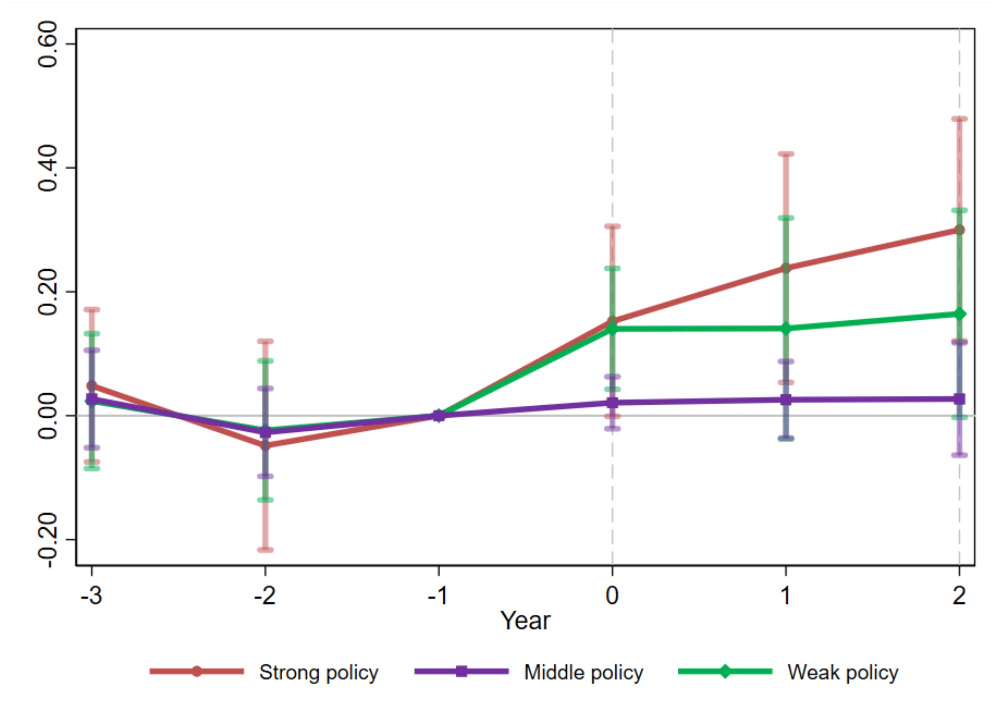

Figure 8: Parallel trend test for the number of carbon-related patents under CT policies

This figure presents the parallel trend test of the number of carbon-related patents in regions with strong (red line), middle (purple line), and weak (green line) CT policies. The two vertical gray dashed lines indicate the announcement date (at year 0) and the implementation date (at year 2), respectively.