Carbon Markets in China: Strategic Interactions and Corporate Adaptation*

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Abstract

Examining a cross section of seven regional Emission Trading System (ETS) and the national ETS in China, we explore the interplay between firms and governments. We find heterogeneous adaptation among firms. Firms in regions anticipating stringent policies reduce emissions and invest in decarbonization technology, whereas expectations of lenient policies lead to increased emissions. Meanwhile, governments set up more stringent carbon policies when firms decarbonize more proactively. The results are robust to allowance allocation policies, such as cap-and-trade or tradable performance standards. Our findings underscore the importance of strategic interactions between firms and governments in decarbonization.

Keywords: Carbon emissions, Carbon markets, Carbon policies, Corporate behavior, Strategic interaction

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

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1 Introduction

To mitigate global warming, governments have adopted a variety of strategies to encourage firms to reduce carbon emissions and invest in low-carbon technologies. Among these, emissions trading schemes (ETS) have emerged as one of the most widely used market-based instruments.[1] ETS transform the right to emit carbon into a tradable asset, thereby creating financial incentives for firms to abate emissions and innovate. Numerous studies explore the design and effectiveness of ETS (Fowlie et al., 2016; Cui et al., 2021, 2018; Jotzo et al., 2018; Guo et al., 2020; Martinsson et al., 2022; Hoppe et al., 2023; Stechemesser et al., 2024). However, most studies only focus on the impact of ETS on firm behavior, while overlooking the reverse channel: how firms' strategic responses shape the evolution of ETS policy design itself.

As carbon markets expand globally, policies are not static but evolve dynamically. On the one hand, firms adjust emissions, production, and innovation in response to government policy. On the other hand, governments update policy stringency in response to observed firm behavior. Given the uncertainty of both emissions and policy (Borenstein et al., 2019), understanding this two-way strategic interaction is essential for evaluating the effectiveness of ETS.

For example, in regions where low-carbon technologies are underdeveloped, imposing stringent carbon policies may be infeasible and economically costly. Local governments therefore tailor policy design to regional economic conditions and technological development. Similarly to the government, firms can also observe regional economic conditions and use current information to predict future policy strictness. If firms expect weak enforcement, they may strategically increase emissions or underinvest in green technologies to influence

[1] 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. In addition, 15 additional programs are planned or under consideration. The growing prevalence of ETS can facilitate the integration of national and regional climate policies, improving global mitigation efforts more efficiently.

future policy. Such dynamics raise a critical question: Do firms manipulate emissions and innovation in anticipation of weak policies, thereby inducing governments to adopt weaker rules? If so, the effectiveness of ETS could be severely compromised. Therefore, understanding the strategic interactions between governments and firms can help us design better carbon emission policies.

We address this question by studying China's carbon markets. China provides an ideal setting for three reasons. First, there are seven regional carbon markets launched in 2013–2014. These regional ETS are largely segmented, with variations in design and enforcement, creating a natural laboratory to observe firm–government interactions. Second,the introduction of the national ETS in 2021, initially covering the power sector, represents a major institutional shift that allows us to study how firms adapt when moving from stricter regional regimes to a more lenient national framework. Third, high-quality data on carbon emissions and green investment such as low carbonization patents are available as firms are required to report actual carbon emissions in China. Our data set allows us to observe the carbon emission data from 2007 to 2023, covering both the policy announcement period (2011), the policy implementation period (2013 and 2014), and the introduction of national ETS markets.

We construct a large dataset and provide a comprehensive study of the impacts of carbon markets on firms in China. We study the evolutions of the interaction between firms and governments. That is, 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. Firm expectations about carbon policies are critical for their corporate decisions. We classify regions ex ante (based on environmental enforcement, environmental budgets, and green ratings) and ex post (based on ETS coverage thresholds and allowance allocation coefficients) into weak, middle, or strong policy regimes. This classification allows us to test how expectations of policy stringency shape firm behavior

Our findings reveal a consistent pattern. After ETS announcements, firms in weak or middle regions strategically increase the level and intensity of emissions, anticipating lenient policies and seeking to secure more allowances. By contrast, firms in strong-policy regions increase investment in carbon-related technologies and generate more patents without increase in emissions, due to the expected tight carbon policies. Stock markets react more strongly to emissions in strong-policy regions, consistent with investors pricing in expected regulatory costs. After implementing regional ETS, only firms in strong-policy regions reduce emissions and increase innovation, which is consistent with the announcement effect. Placebo tests confirm that these effects are concentrated among ETS-regulated firms. This shows that the observed corporate responses from ETS-regulated firms to the implementations of ETS markets are not driven by confounding regional shocks or general time trends. We also find that governments adjust policy stringency in response to corporate actions: regions with more green innovation subsequently impose stricter policies (e.g., reducing carbon allowances, imposing restrictive parameters in carbon allowance allocation), while regions with higher emissions relax them.

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 similar effects with CT and TPS. They are both effective in motivating firms to decarbonize and increase green investment in regions with strong policies. But stock markets react more strongly under CT policy.

The introduction of the national ETS in 2021 further illustrates these dynamics. The national ETS in 2021 includes all firms in the power industry with annual emissions exceeding 26,000 tons of CO_2. Currently, the national ETS imposes less stringent requirements than all regional pilot markets. Therefore, firms in the power industry that previously were covered in regional carbon markets face looser carbon policies in the national ETS. We find that power firms in weak-policy regions increase emissions after transitioning to the national ETS, while non-power firms in the same regions decrease their emissions, as local governments tightened oversight to offset the power sector's increase in order to meet their regional carbon reduction goal, e.g., the spill-over effect across industries.

By highlighting the feedback loop between firms and governments, our study contributes to several strands of literature. Firstly, we contribute to the literature on emission trading markets. Previous studies evaluate the effectiveness of ETS without considering the effects of the announcement, firms' expectations, and the endogeneity of the policy design (Bayer and Aklin, 2020; Cui et al., 2021). The most relevant paper for our study is Biais and Landier (2022). Biais and Landier (2022) provide a theoretical model that supports 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. In contrast, if firms anticipate weak carbon policies and invest less in green technologies, then governments will find imposing weak carbon policies to be optimal. Due to the flexibility of regional policy design, China's regional ETS pilot programs provide an ideal setting to test the model of Biais and Landier (2022). Our empirical results support the predictions in Biais and Landier (2022).

Secondly, our paper is related to the literature specifically on China's ETS. Previous studies explore the allocation policy of carbon allowances (Lin and Jia, 2018), the impacts of ETS on coal consumption and efficiency for power plants (Cao et al., 2021), economic growth (Fan et al., 2016; Liu et al., 2017), pollutant emissions (Li et al., 2018), green innovation (Zhu et al., 2019; Weng et al., 2022), and firm performance (Luan et al., 2025). These studies often rely on computational simulations or examine the impacts of ETS at the aggregate level. We add to the literature by considering the heterogeneity of the strictness of carbon policy between regions and providing firm-level evidence.

Third, we contribute to the literature that examines the impacts of carbon risk on corporate behavior and its pricing. Carbon risk affects corporate policies such as leverage, bank loan, cash holdings, and green investment (Shive and Forster, 2020; Antoniou et al., 2022; Sautner et al., 2023a; Ginglinger and Moreau, 2023; Li et al., 2024). The empirical evidence for 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; Sautner et al., 2023b), bonds (Huynh and Xia, 2021; Seltzer et al., 2022; Cao et al., 2025), derivatives (Ilhan et al., 2021), and bank loans (Bartram et al., 2022; Ivanov et al., 2024; Martini et al., 2023), suggesting a premium for carbon risk. 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, 2025; Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang, 2021; Duan, Li, and Wen, 2025; Aswani, Raghunandan, and Rajgopal, 2024). The inconclusive evidence is mainly due to two limitations in previous studies. One is data quality and availability (Zhang, 2025). Another limitation is that previous studies examined carbon pricing from the perspective of very few (often one) market participants, without considering interactions among various market participants. When the externality of carbon emissions 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 truly reported carbon emission data and 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 the 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 in varying economic contexts, thereby facilitating the implementation of a national 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, which include five cities (Beijing, Shanghai, Tianjin, Chongqing, and Shenzhen) and two provinces (Guangdong and Hubei), i.e., seven pilot regions. 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 the power industry was introduced, covering more than 40% of China's CO_2 emissions (Ministry of Ecology and Environment, 2024). Currently, China's carbon emission markets have become the largest carbon trading markets worldwide. These seven pilot programs operated independently of each other. Different regions have discretionary power to decide the policy and coverage of carbon allowance allocation, which we will discuss below.

2.1 Carbon allowance allocation policies

Carbon allowance allocation policies directly affect carbon prices and restrictions on firms. 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 usually based on its historical emission levels before the compliance period. 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, the allowance of the firm i in year t in region k is given by

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

where $HistoricalEmission$ refers to historical emissions of firm i before year t (e.g., historical emissions over five-years) and $\beta_{TPS,k}$ is the CT coefficient in region k.

[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.

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.

Clearly, the coefficients $\beta_{CT,k}$ and $\beta_{TPS,k}$ capture the stringency of the 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 the region k. Appendix A summarizes the carbon allocation policy in each region in China. 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.

2.2 Coverage

In addition to different carbon allocation policies, 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 2010 or 2011 were included in Hubei ETS. In contrast, Beijing's 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 establish local carbon policies, it is important to compare the strictness of policy between regions. In addition, carbon policies are usually not disclosed before ETS trades, so firms have to choose carbon emission levels based on their expectations of carbon policies. After local ETS is implemented, firms know the local carbon policies. Therefore, from the firm perspective, we employ an ex ante information set to predict future policy strictness before ETS starts and use ex post policy disclosed to measure policy strictness after 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 the local carbon ETS.

First, we used the average air pollution fees and total pollution fees of publicly listed firms during 2009–2011 to proxy for the intensity of firm-level environmental enforcement. 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, Guangdong, and Shanghai) as strong regions while the rest three regions as weak ones.

Second, we use local government expenditure on environmental protection in 2009-2011 to measure the intensity of environmental investment 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., Beijing, Shenzhen, Guangdong, and Hubei) as strong regions while the other three regions as weak.

Third, we use the City Green Development Index Rankings as third-party ratings. 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 cities that participated 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

[3] See Appendix B for the details.

[4] See Appendix C for details.

are 19 cities that scored below the average level in green development. Therefore, we classify Beijing and Shenzhen as strong regions while the remaining five regions as weak ones, based on this ranking.

We use these three ex ante measures to proxy for firms' expectations about local carbon policies. One might wonder whether these three measures could be influenced by firms before ETS announcements. For example, pollution fees may be affected by firm lobbying or evasion. There is little concern about this as we aim to examine the incremental effects of ETS on corporate adaption.

Table 1 summarizes these three ex ante measures in Columns (1)–(3), respectively. Column (4) provides a 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 a regional ETS was implemented, the local government issued detailed carbon policies to the public, including the coverage threshold and the carbon allowance allocation policy. Therefore, we can cross check the policy strictness measure, which uses ex ante information with the ex post carbon policy.

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 include firms in local ETS, use different allowance allocation policies (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 strictness of policy between 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 in 2009-2012. That is, firms in Tianjin with average carbon emissions greater 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. For this measure, we sort all regions based on their thresholds and classify a region as strong if its threshold is below the median across all regions.

Next, we compare the coefficients used in the TPS or CT carbon allowance policies. 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 if its coefficient is below the median across all regions.

Finally, we summarize the policy strictness of these three measures (including the 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 build a comprehensive database. See Appendix D for details about variable denitions and data sources.

1. **China National Tax Survey Data (CNTSD)**: The database encompasses panel data at the plant level that spans 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. In addition, the database includes extensive environmental metrics. It includes the amount of coal, natural gas, and oil used; the amount of sulfur dioxide (SO_2), nitrogen oxides (NO_x), 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 (NO_x) emissions, sulfur dioxide (SO_2) 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 geographic coordinates (latitude and longitude).

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

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

    - **Carbon Emission Market Company Information**: This dataset provides information on the companies that participate 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 are 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 to estimate the difference in the difference between subgroups (DiD) (De Simone et al., 2024). Firms included in the regional pilot 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. That is, there are two treatments, e.g., announcements and implementations. We extend the standard DiD method to show heterogeneous effects on corporate behavior under different environmental policy strictness. We use three treatment dummies, i.e., Strong, Middle, and Weak, to indicate 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 seven regions before the announcements (implementation) of the 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 in year t; $Strong_i$, $Middle_i$, 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; $\epsilon_{i,t}$ is the error term. We are interested in the impacts on carbon emission, carbon emission intensity, production, production equipment, labor, and the number of decarbonization-related patents. β_1, β_2, and β_3 show the average treatment effects of ETS announcements or implementations on firms under different policy strictness.

For robustness, we also perform a standard triple DiD to examine the announcement or implementation effects of pilot ETS on corporate behavior, as follows:

$$y_{i,t} = \beta_1 Treatment_i \times Post_t + \beta_2 Treatment_i \times Post_t \times Strong_i + \beta_3 \eta_i + \beta_4 \sigma_t + \epsilon_{i,t}, \quad (4)$$

where $y_{i,t}$ is the outcome variable of interests for firm i in year t; $Treatment_i$ 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; η_i represents firm-level fixed effects and σ_t represents year-fixed effects; $\epsilon_{i,t}$ is the error term. The triple DiD allows us to compare the treatment effects in regions with strong and non-strong (e.g., weak or middle) environmental policies.

4.2 Matched DiD estimation

The treated and untreated firms in a pilot region are not perfectly comparable because only the firms with high emissions are covered in the pilot market, while the firms with low emissions are not. Therefore, the emission level and the size of the treatment group are usually larger than those of the untreated firms from the same region. Therefore, we cannot use treated and untreated firms from the same pilot region as matched samples. One would suggest using variations between regions for identification. However, this would lead to a biased result if the firms differ significantly in their pretreatment 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 ETS announcement) and select 20 untreated firms as the matched sample. Figure 1 plots the geographical distribution of the treated firms and the matched firms.

5 Results

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

5.1 Corporate responses to carbon policies

5.1.1 Announcement effects of regional ETS

We first run a panel regression of Equation (3) to examine the announcement effects of the regional pilot ETS markets. That is, the treatment in Equation (3) is the announcement of the introduction of 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.

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

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 strong environmental policies. This is consistent with Fan et al. (2016), Liu et al. (2017), and Luan et al. (2025) that ETS promote economic growth and firm performance. Second, Columns (1)–(2) show that treated firms located in regions with middle or weak environmental policies actually increase their carbon emissions, at both levels and emission intensity. This suggests that these firms intend to signal their carbon emission status, intending to gain some advantage (e.g., receiving more carbon allowances) during the implementation stage of the local ETS later. Last, Column (6) shows that treated firms located in regions with strong environmental policies increase their carbon-related patents, suggesting that these firms invest more in decarbonization technology. But we do not see the impacts on green innovation for firms in regions with weak policies.

Figure 2 further 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 matched firms from non-pilot regions. The model-free mean plot shows a clear pattern that firms expecting strong environmental policies will invest more in decarbonization technology. Zhu et al. (2019) and Weng et al. (2022) show that ETS promotes green innovation, but our evidence shows that this only occurs in regions with strong environmental policies.

For robustness checks, we also perform a standard triple DiD test in Appendix E and Table E.4, 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 a clear pattern across policy strictness. We see that the announcements of the pilot ETS do not negatively affect corporate production. If treated firms expect a weak policy, firms will tend to strategically increase their carbon emissions 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 strategic interactions between firms and local governments.

5.1.2 Implementation effects of regional ETS

Next, we run a 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 carbon policies are now disclosed to companies, we use the ex post measure of strictness of carbon policies to differentiate these seven pilot regions, see, e.g., Table 2.

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

Table 5 reports the panel regression results from the matched sample. We see that both the emission level (Column (1)) and the emission intensity (Column (2)) decrease for treated firms located in regions with strong carbon policies, but no impacts on firms in regions with middle and weak carbon policies. Columns (3)–(5) show insignificant impacts of pilot ETS on corporate production, which is similar to the announcement effects observed in Columns (3)–(5) of Table 4. Column (6) shows that ETS has a significant impact on carbon-related patents for firms in regions with strong carbon policies.

For robustness check, we also perform a standard triple DiD test in Appendix E. Table

E.5 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 levels and intensity of carbon emission, and invest more in carbon-related patents after implementing a pilot ETS, which is similar to those reported in Table 5.

5.1.3 Placebo test

To further verify that the implementation effects are specific to ETS-regulated firms rather than reflecting broader contemporaneous shocks, we perform a placebo test over firms within pilot regions. However, non-ETS firms might respond to the implementations of regional ETS as they may be expected to be included in ETS markets later. To rule out such a signaling effect, we carefully select a placebo group of non-ETS firms that are unlikely to be included in carbon markets in the near future. Specifically, we select firms that: (i) operate in non-ETS industries but are located in pilot regions; and (ii) have carbon emissions below 25% of the region-specific coverage threshold for the carbon market. For example, since the coverage threshold in Beijing is 10,000 tons of CO_2, we use firms with annual emissions below 2,500 tons as the placebo pool in Beijing.

Even after this screening, the placebo pool remains large and includes many small firms, raising concerns about comparability. To address this issue, we further refine the placebo group using propensity score matching (PSM), following the same matching strategy used before. For each treated firm, a placebo firm is selected from the same pilot region and non-ETS sector. We match firms by the logarithm of emissions, the logarithm of emission intensity, and the logarithm of production, using pre-treatment data, and employ a one-to-one nearest-neighbor match.

We then estimate the implementation effects over the placebo sample, using the matched DiD specifications applied in Section 5.1.5. Table 6 reports the DiD estimation results. There are no statistically significant responses among placebo firms in regions with different levels of policy stringency. This null effect supports our identification strategy, indicating that observed corporate responses are concentrated among ETS-regulated firms rather than being driven by confounding regional shocks or general time trends.

5.1.4 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 chosen endogenously, given the strategic interaction between local governments and firms. That is, pilot regions endogenously chose TPS or CT for certain industries. We use instrumental variables to address this endogeneity issue. We observe that to implement TPS, local governments need to have information on firm production. That is, the availability of production information is critical for local governments to decide whether to use TPS or not. However, such information may not be available to local governments in China for several reasons. First, firms, especially nonlisted firms, may not be required to disclose their production information. Second, firms often have strong incentives to hide their production information for tax avoidance purposes. In practice, local governments rely on reports from the National Bureau of Statistics of China to collect information about firm production. The China National Bureau of Statistics requires companies above the designated size to report their production. During 2007-2010, the designated size was RMB 5 million. That means that local governments have production information of a firm if its size is more than RMB 5 million. This suggests that firms with a size greater than RMB 5 million are more applicable to TPS. This threshold is decided by the central government, so it is exogenous to firm behavior. 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:

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

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); $\epsilon_{i,t}$ is the error term. 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:

$$y_{i,t} = \beta_1 \widehat{TPS}_{i,t} \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \varepsilon_{i,t}, \tag{6}$$

where $y_{i,t}$ is the outcome variable of interests for firm i in year t; $Post_t$ 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; $\varepsilon_{i,t}$ is the error term. 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 (5) and (6) by CT.

Table 7 reports the results from the first-stage regression. To verify our choice of 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. In fact, we see that only the threshold of RMB 5 million is statistically significant at the 10% level. This validates our instrumental variable.

Table 8 presents the second-stage regression results, examining the implementation effects of ETS with TPS allocation policies. Panels A and B show that in regions with strong and middle carbon policies, TPS decreases the level of carbon emission (in Column (1)) and the intensity of carbon emission (in Column (2)). Carbon-related patents also increase in Column (6). However, Panel C shows that in regions with weak carbon policies, carbon emission level or intensity does not change significantly under TPS.

Table 9 presents the second stage regression results, examining the effects of ETS implementation with CT allocation policies. Panel A shows that in regions with strong carbon policies, CT reduces both carbon emission level (in Column (1)) and carbon emission intensity (in Column (2)), while there are no significant impacts in regions with weak carbon policies. Firms also increase carbon-related patents in regions with a strong carbon policy.

Overall, we find similar results under CT and TPS. Importantly, we see that the strictness of the carbon policy matters a lot. In regions with strict carbon policies, TPS and CT can reduce both levels of emission and intensity, while there are no impacts in regions with weak policies. It is necessary to impose a strict carbon policy to achieve the goal of reducing carbon emissions and promoting carbon-related innovation.

5.1.5 Implementation effects of national ETS

In 2021, China launched its national carbon emissions trading scheme (ETS), which covers all firms in the power industry 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 implementation of the national ETS 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 perform the difference-in-difference method in the power industry using the following regression:

$$Emission_{i,t} = \beta_1 PilotRegion_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{7}$$

where $Emission_{i,t}$ is the logarithm carbon emission for firm i in year t; $PilotRegion_i$ 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; $\epsilon_{i,t}$ is the error term.

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

$$Emission_{i,t} = \beta_1 Strong_i \times Post_t + \beta_2 Middle_i \times Post_t + \beta_3 Weak_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{8}$$

where $Emission_{i,t}$ is the logarithm carbon emission for firm i in year t; $Strong_i$, $Middle_i$, 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; $\epsilon_{i,t}$ is the error term. β_1, β_2, and β_3 capture the average treatment effects of the implementation of the national carbon ETS on firms located in regions with different policy strictness.

Table 10 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 to power industry firms in non-pilot regions after transferring to the national ETS. Column (2) shows that such an increase is mainly driven by firms in pilot regions with weak policy strictness. In fact, to include power firms from all regions, the national ETS has lower regulatory stringency than those pilot 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. However, 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 after moving from regional to national ETS.

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 (7) and (8), we study other carbon-intensive sectors, including manufacturing, iron and steel production, and aviation industries. Limited by data availability, we 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 are no significant changes in carbon emissions in most pilot regions, regions with weak carbon policies exhibit a significant decrease 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, local governments strengthened their oversight of non-power sectors to maintain overall emission targets.

[6]For power firms, 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.

5.2 Governments' responses to corporate actions

Given the strategic actions of firms, how would the government set up carbon policies? We employ the following regression to investigate this issue:

$$PolicyStringency_{i,t} = \beta \; CorporateAction_{i,t-1} + \gamma \; Controls_{i,t-1} + \varepsilon_{i,t} \tag{9}$$

where $PolicyStringency_{i,t}$ represents the stringency of carbon policies in region i and year t; $CorporateAction_{i,t-1}$ denotes corporate actions of carbon emission in region i and year $t-1$; $Controls_{i,t-1}$ is a set of control variables that could affect carbon policies, including local GDP and other pollution fees charged. We measure corporate actions of carbon emission for firms participating in the carbon markets in three ways, including carbon patent, carbon emission level, and carbon emission intensity. Independent variables are lagged by one year to capture the decision-making process of local governments.

In Panel A of Table 11, we use the average carbon allowance per firm to measure the stringency of carbon policies, which is calculated as the total carbon allowances divided by the total number of firms participating in the carbon markets. This captures the overall stringency of carbon policies in a region. Column (1) indicates a significantly negative coefficient of lagged carbon-related patents, suggesting that regions with higher average carbon-related patents in the previous year tend to implement more stringent policies, e.g., allocating a lower carbon allowance. Columns (2) and (3) indicate a positive yet insignificant coefficient of lagged carbon emission or carbon emission intensity.

Next, we examine TPS or CT allocation policies to analyze the results at a granular level. We use the TPS coefficient and the CT coefficient to measure the stringency of the policy in Panels B and C of Table 11, respectively. A lower TPS or CT coefficient represents more stringent carbon policies. We see that higher carbon-related patents in the previous year lead to more stringent carbon policies, e.g., a lower TPS coefficient in Column (4) and a lower CT coefficient in Column (7). Similarly, higher carbon emission or carbon emission intensity leads less stringent carbon policies, e.g., a higher TPS coefficient in Columns (5) and (6), or a higher CT coefficient in Column (8).

In general, Table 11 reveals a consistent and strategic pattern across policies, demonstrating how local governments adjust the stringency of the carbon policy in response to corporate actions.

5.3 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. Similarly to Zhang (2025), we perform the following regressions:

$$
\begin{aligned}
r_{i,t} &= \alpha + \beta\, Lagged\ Emission_{i,t} + \gamma Controls_{i,t} + \beta_2 \eta_i + \beta_3 \sigma_t + \varepsilon_{i,t}, \\
r_{i,t} &= \alpha + \beta\, Lagged\ Emission\ Intensity_{i,t} + \gamma Controls_{i,t} + \beta_4 \eta_i + \beta_5 \sigma_t + \varepsilon_{i,t},
\end{aligned}
\tag{10}
$$

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 firm i; control variables ($Controls_{i,t}$) 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; $\varepsilon_{i,t}$ is the error term. We lag carbon emission level and intensity by 18 months to ensure the data is available to the markets (Zhang, 2025).

An 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:

$$PolicyExposure_{i,t} = \sum^{j \in J} \frac{1}{Rev_{i,t}} (3 \times Strong_{j,t} \times Rev_{j,t} + 2 \times Middle_{j,t} \times Rev_{j,t} + Weak_{j,t} \times Rev_{j,t}), \tag{11}$$

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:

$$CTRatio_{i,t} = \sum^{j \in J} \frac{1}{R_{i,t}} (CT_{j,t} \times R_{j,t}), \tag{12}$$

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 Equation (12) by TPS.

We sort all listed companies into tercile portfolios, based on $PolicyExposure_{i,t}$ and categorize the companies into three groups: Strong, Middle, and Weak. Then we run regressions of the Equation (10) for the full sample or each group to examine the reactions of the stock market to carbon emissions. Table 12 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 of carbon emission after announcing pilot carbon markets, but no market reactions before the announcements, while there is some weak evidence in the intensity of emissions 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 did not respond to carbon emission in regions with weak policies.

Next, we investigate the differential reactions of stock prices to carbon emissions under different allowance allocation policies. We categorize the 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. Table 13 presents the regression results. We can see that most of the market reactions come from CT policies, not TPS policies. This suggests that CT constrains corporate production more.

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 of regional ETS markets, and after introducing the national ETS markets. We study corporate behavior (e.g., carbon emission levels and intensity, firm production, and carbon-related patents), government policies, and stock market reactions surrounding the carbon markets.

We find that firms in regions with strong policies decrease carbon emission level and intensity, and increase carbon-related patents given the expected tight carbon policies, but no significant reductions of carbon emissions for firms in regions with weak policies as they foresee weak requirements imposed by the local governments. Meanwhile, governments set up carbon policies according to corporate responses. We find that when firms proactively take green steps, e.g., investing more in carbon-related patents or reducing carbon emissions, governments respond with more stringent carbon policies. The results are robust to different allowance allocation policies, e.g., CT and TPS. We also find supporting evidence from stock market reactions.

The strictness of carbon policies is critical to carbon reduction. These findings underscore the critical role of strategic actions between firms and governments 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 actions. 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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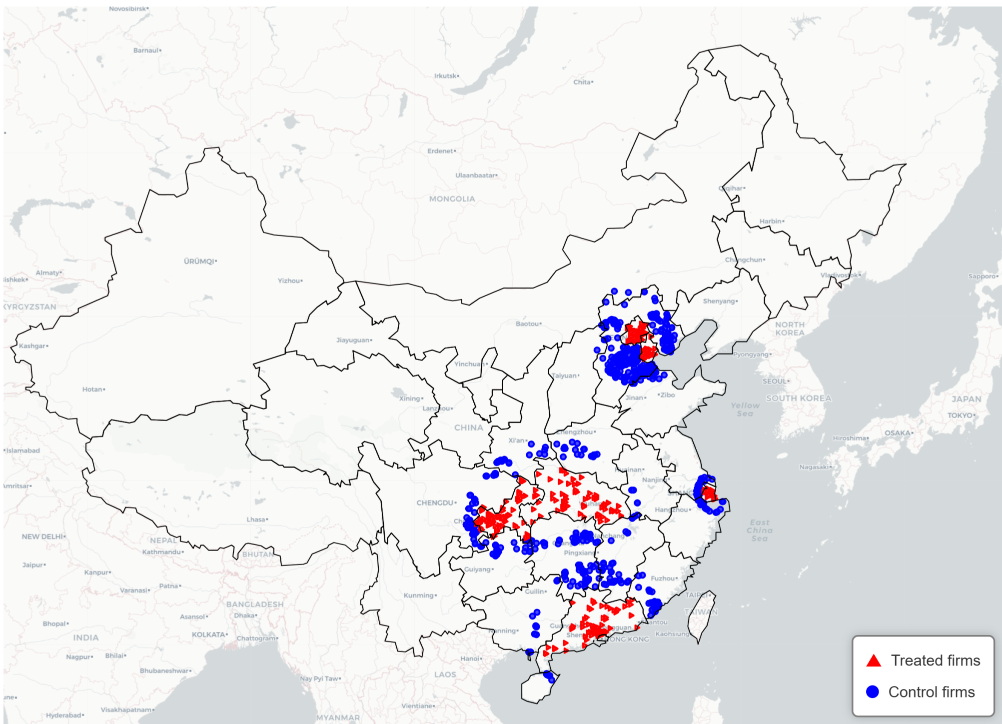

Figure 1: Geographical distribution of treated and matched firms

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

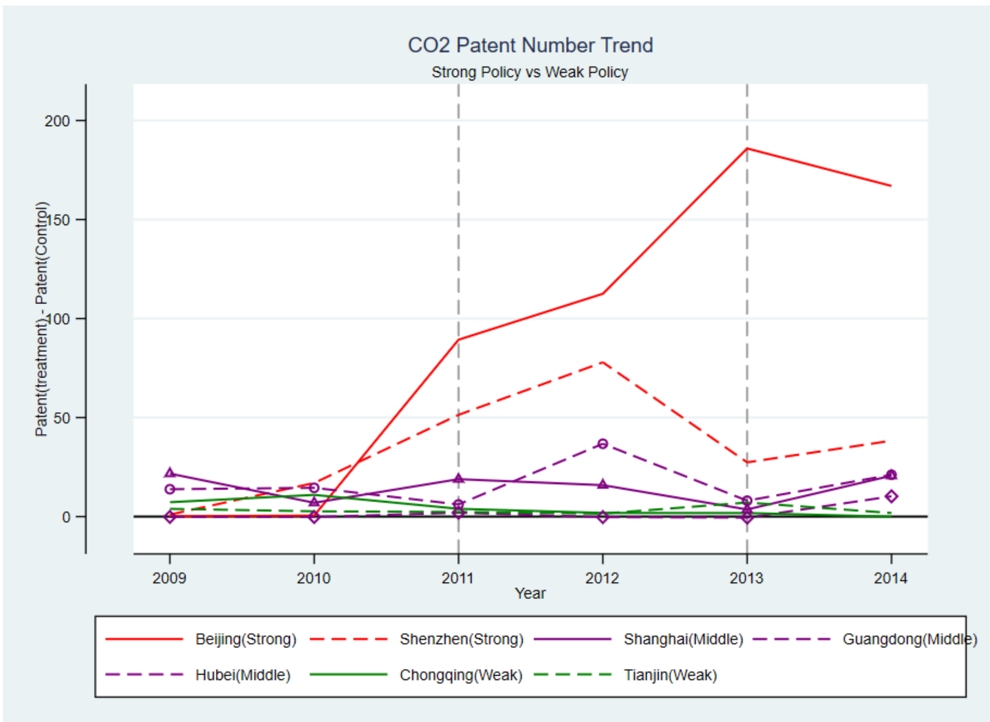

Figure 2: The average number of decarbonization-related patents

This figure plots the average number of patents related to decarbonization from firms with strong (the red lines, e.g., Beijing and Shenzhen), middle (the purple lines, e.g., Shanghai, Guangdong, Hubei), and 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 the control groups from the non-pilot regions.

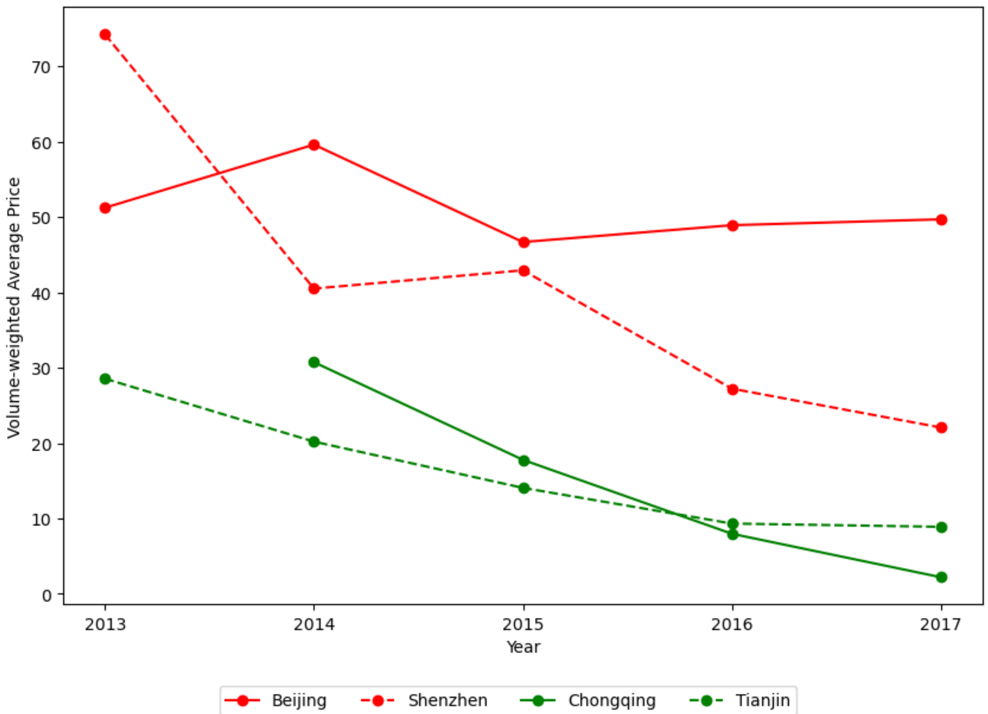

Figure 3: Average annual carbon prices

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 with 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)). 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	Strong	Strong	Strong	Strong
Shenzhen	Strong	Strong	Strong	Strong
Guangdong	Strong	Strong	Weak	Middle
Shanghai	Strong	Weak	Weak	Middle
Hubei	Weak	Strong	Weak	Middle
Chongqing	Weak	Weak	Weak	Weak
Tianjin	Weak	Weak	Weak	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)). 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	Strong	Strong	Strong	Strong
Shenzhen	Strong	Strong	Strong	Strong
Guangdong	Strong	Weak	Weak	Middle
Shanghai	Strong	Weak	Strong	Middle
Hubei	Weak	Strong	Weak	Middle
Chongqing	Weak	Weak	Weak	Weak
Tianjin	Weak	Weak	Weak	Weak

Table 3:
Summary statistics

This table reports the summary statistics of treated and matched 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	101,589	8.051	2.781	5,000	9.726	2.650
Carbon emission intensity	88,961	-2.389	3.530	4,596	-1.416	5.308
Production	107,594	10.902	2.068	6,749	12.418	1.802
Production equipment	129,269	9.410	2.484	9,213	11.496	2.064
Labor	135,078	4.976	1.679	9,527	6.506	1.484
Carbon patents	136,827	0.512	1.132	10,864	1.075	1.512

Table 4:
Corporate responses to the announcements 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 errors 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 (firm-fixed effects and year-fixed effects) are included. ***, **, * 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	-0.0429	-0.327	0.837***	0.0663*	0.130***	0.825***
	(0.0692)	(0.198)	(0.197)	(0.0293)	(0.0331)	(0.0409)
Middle Policy	1.542***	1.723**	0.383	0.187	0.0866	0.389**
	(0.297)	(0.622)	(0.870)	(0.101)	(0.0792)	(0.119)
Weak Policy	0.676**	1.653***	-0.129	0.0779	0.170*	0.0943
	(0.261)	(0.451)	(0.659)	(0.0916)	(0.0853)	(0.124)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	60623	60623	83110	80198	82943	83110

Table 5: Corporate responses to the implementations 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 errors 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 (firm-fixed effects and year-fixed effects) are included. ***, **, * 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	-1.402***	-1.670***	-0.372	0.0145	-0.0367	0.168***
	(0.178)	(0.325)	(0.257)	(0.0570)	(0.0589)	(0.0284)
Middle Policy	0.113	-0.171	1.354	-0.445	-0.576	0.195
	(0.596)	(0.617)	(1.029)	(0.401)	(0.356)	(0.149)
Weak Policy	0.0375	-0.100	-1.189	0.0453	0.0790	0.0413
	(0.177)	(1.000)	(0.864)	(0.0391)	(0.0835)	(0.0751)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	114002	114002	123634	122128	123360	123634

Table 6: Corporate responses to the implementations of regional ETS: A placebo test

This table reports placebo test results for implementation effects of regional ETS on corporate outcome, using the difference in difference method over the period from 2011 to 2016. Corporate outcome variables include 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 errors 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 (firm-fixed effects and year-fixed effects) are included. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Production Equipment	(5) Labor	(6) Patent
Strong Placebo	-0.178	0.320	-0.0900	-0.0474	0.104*	0.104
	(0.314)	(0.540)	(0.229)	(0.0818)	(0.0419)	(0.0896)
Middle Placebo	-0.0481	0.226	0.282	-0.0454	0.0905	0.0861
	(0.214)	(0.381)	(0.204)	(0.111)	(0.0625)	(0.0603)
Weak Placebo	0.0176	0.555	-0.615	-0.0622	0.0480	0.0473
	(0.366)	(1.082)	(0.431)	(0.140)	(0.125)	(0.179)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	45550	38298	43519	50064	50620	50908

Table 7: First-stage regression of TPS allocation policy

This table presents the first-stage regression results for the instrumental variable 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 errors 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	0.176*					
	(0.0687)					
10 million		0.104				
		(0.0653)				
15 million			0.0714			
			(0.0634)			
20 million				0.0509		
				(0.0623)		
25 million					0.00680	
					(0.0607)	
30 million						-0.0227
						(0.0596)
Other Controls	Y	Y	Y	Y	Y	Y
N	5466	5466	5466	5466	5466	5466

Table 8:
Corporate responses to the implementations 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 errors 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 (firm-fixed effects and year-fixed effects) are included. ***, **, * 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						
	-1.186***	-1.535***	-0.165	0.180	0.950	0.640*
	(0.0670)	(0.0847)	(0.334)	(0.135)	(0.519)	(0.286)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	18871	18871	18052	20554	20780	20879
Panel B: Regions with middle carbon policies						
	-2.426***	-3.563***	0.482**	0.126	0.205**	-0.0734
	(0.264)	(0.393)	(0.154)	(0.173)	(0.0770)	(0.212)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	18871	18871	18033	20535	20760	20859
Panel C: Regions with weak carbon policies						
	0.326	0.341	-0.345	0.128	0.106**	0.383
	(0.389)	(0.294)	(0.0984)	(0.131)	(0.0369)	(0.290)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	18872	18872	18038	20534	20759	20858

Table 9:
Corporate responses to the implementations 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 errors 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 (firm-fixed effects and year-fixed effects) are included. ***, **, * 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						
	-1.381***	-1.799***	0.195***	0.0326	-0.0604	0.234***
	(0.180)	(0.302)	(0.0512)	(0.0495)	(0.0356)	(0.0694)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	139786	139786	136116	155899	157676	158088
Panel B: Regions with middle carbon policies						
	0.0631	-0.481	0.446	-0.611	-0.471	0.120
	(0.199)	(0.375)	(0.731)	(0.431)	(0.374)	(0.117)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	139090	139090	134865	154373	156125	156526
Panel C: Regions with weak carbon policies						
	-0.0520	0.641	-0.606**	-0.00245	0.141	0.0544
	(0.139)	(1.412)	(0.227)	(0.0721)	(0.0742)	(0.110)
Fixed Effects	Y	Y	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y	Y	Y
N	139120	139120	134900	154388	156140	156541

Table 10: Corporate responses to the implementations of national ETS

This table examines the impacts of national ETS 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 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 (firm or region-fixed effect, and year-fixed effect) are included. 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

Table 11: Governments' responses to corporate actions

This table examines how local governments set up the stringency of carbon policies based on regional conditions. We measure the stringency of carbon policies in three ways: allowance per firm in Panel A, which is the total allowance divided by the number of firms participating in carbon markets; TPS Coefficient in Panel B; and CT Coefficient in Panel C. The key independent variables include carbon patent (the average number of carbon-related patents by firms participating in the carbon markets), carbon emission (average carbon emissions of firms participating in the carbon market), and carbon emission intensity (average carbon emission intensity of firms participating in the carbon markets. Panel B or C uses firms under TPS or CT allowance allocation policy. Control variables include GDP and other pollution fees. All explanatory variables are lagged by one year. Standard errors are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Allowance per firm			Panel B: TPS coefficient			Panel C: CT coefficient		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged carbon patent	-0.00002**			-1.135***			-0.017**		
	(0.000)			(0.291)			(0.006)		
Lagged carbon emission		0.00053			0.324***			0.011***	
		(0.001)			(0.077)			(0.004)	
Lagged carbon emission intensity			0.00043			0.232***			0.005
			(0.001)			(0.073)			(0.004)
Lagged GDP	0.004*	0.004	0.004	0.565	0.753**	0.781**	0.020*	0.007	0.017
	(0.002)	(0.003)	(0.003)	(0.394)	(0.271)	(0.305)	(0.011)	(0.011)	(0.012)
Lagged other pollution fees	-0.001	0.001	0.001	0.624**	-0.088	0.031	-0.026**	-0.028***	-0.023**
	(0.002)	(0.003)	(0.002)	(0.267)	(0.231)	(0.254)	(0.010)	(0.009)	(0.010)
N	23	23	23	16	21	21	25	27	27

Table 12: 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 errors 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.

	Carbon emission levels			Carbon emission intensity		
	before announcements Feb 2007–Sep 2010 (1)	after announcements Oct 2010–May 2014 (2)	after implementation Jun 2014–Feb 2017 (3)	before announcements Feb 2007–Sep 2010 (4)	after announcements Oct 2010–May 2014 (5)	after implementation Jun 2014–Feb 2017 (6)
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 13: 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 (B or C) uses a subsample of firms under 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 errors 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.

	Carbon emission levels			Carbon emission intensity		
	before announcements Feb 2007–Sep 2010 (1)	after announcements Oct 2010–May 2014 (2)	after implementation Jun 2014–Feb 2017 (3)	before announcements Feb 2007–Sep 2010 (4)	after announcements Oct 2010–May 2014 (5)	after implementation Jun 2014–Feb 2017 (6)
Panel A: 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 B: 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 C: 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

Online Appendix

A Carbon allowance allocation policy

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

B Pollution fees

Table B.1: 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

C Government Expenditure on Environment Protection

Table C.2: 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

D 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 emissions come from the consumption of purchased electricity or heat. For each firm, direct carbon emissions are calculated by multiplying the consumption of each energy type by its carbon emission factor, which is summarized in Table D.3.

Table D.3: 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 mainly 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 2007 to 2016.

Production Production is measured by the total value of industrial production, 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 as logarithmic thousands of RMB. The sample period is 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, the intensity of carbon emissions is equal to the carbon emission divided by production. The sample period is 2007 to 2016.

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

Production Equipment Production equipment is proxied by investments in specialized production machinery and equipment, derived from CNTSD. Specifically, the measurement uses 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 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 used as one of the matching variables in our empirical analysis. The sample period is 2007-2016.

Treatment The information of the treated firms in each pilot region is primarily sourced from the China Stock Market & Accounting Research Database (CSMAR) database, which provides the company name, the unified social credit identifier, the 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. Data collection covers the period 2009-2011.

Carbon Price Carbon price data is extracted from the CSMAR database, which provides daily trading information for carbon emission allowances in 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 2013 to 2016.

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

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:

$$y_{i,t} = \beta_1 Treatment_i \times Post_t + \beta_2 Treatment_i \times Post_t \times Strong_i + \beta_3 \eta_i + \beta_4 \sigma_t + \epsilon_{i,t}, \quad (13)$$

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; η_i represents firm-level fixed effects and σ_t represents year-fixed effects. We are interested in the impacts on carbon emission, carbon emission intensity, production, production equipment, labor, and the number of decarbonization-related patents.

Table E.4 reports the results of the panel regression of the announcement effects. The significantly positive coefficients of the interaction term of *Post* and *Treatment* (e.g., $Post \times Treatment$) in Columns (1) and (2) indicate that firms in regions with weak or middle environmental policies strategically increased their level and intensity of carbon emission after ETS 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., $Post \times Treatment \times Strong$) in carbon emission and emission intensity indicate 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.4:
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 (firm-fixed effects and year-fixed effects) are included. ***, **, * 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 × 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 × Treatment × 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.5:
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 (firm-fixed effects and year-fixed effects) are included . ***, **, * 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 × 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 × Treatment × 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