Strategic Interactions and Corporate Adaptation in Carbon Markets*

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Abstract

Carbon emission trading systems evolve through repeated interaction between firms and regulators. Firms anticipate future stringency before regulators commit, and regulators adjust stringency after observing firm responses. Using China's seven regional pilot emission trading systems (ETS) and the subsequent national ETS, we document this two-way feedback. Firms in regions anticipating stringent enforcement reduce emissions and increase decarbonization patents. Firms expecting leniency expand emissions, consistent with strategically inflating the historical baselines used to allocate future allowances. Local governments tighten allowance allocations where firms innovate more and loosen them where firms emit more. The pattern is robust to alternative allocation designs (cap-and-trade or tradable performance standards), and to a firm-level expectation measure constructed from investor relations transcripts. The findings highlight a feedback loop that can weaken policy stringency under regulatory discretion.

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

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1 Introduction

Emission trading systems (ETS) are the dominant market-based instrument for reducing carbon emissions worldwide. ETS programs cover roughly 18% of global emissions across more than twenty active jurisdictions (World Bank, 2024).[1] An extensive literature evaluates these programs as discrete regulatory interventions, asking whether implementation reduces emissions or stimulates innovation (Fowlie et al., 2016; Bayer and Aklin, 2020; Cui et al., 2021; Martinsson et al., 2022; Calel and Dechezleprêtre, 2016; Stechemesser et al., 2024). This view abstracts from a feature that is central in practice. ETS rules are not announced and implemented in isolation, but are designed through repeated interaction between firms that anticipate future stringency and regulators that adjust stringency after observing firm responses.

This interaction matters for policy effectiveness. Biais and Landier (2022) model an ETS in which firms invest in low-carbon technology before regulators commit to allowance caps. Their model predicts strategic complementarity between firm investment and regulatory stringency. When firms invest more, regulators find it optimal to tighten policy. When firms invest less, regulators find it optimal to loosen policy. Firm expectations about future policy, which depend on observable signals about local environmental policies, shape firm investment and therefore the realized policy through this two-way channel. We focus on documenting this two-way feedback. Empirical evidence on the two-way mechanism is sparse, partly because most ETS programs apply uniform rules across firms within a jurisdiction and partly because firm-level variation in expected policy is hard to measure.

We exploit institutional features of China's regional carbon pilots to document this interaction directly. Between 2013 and 2014, seven regions launched ETS pilots under a single central directive but with substantial regional discretion over policy design. Inclusion thresholds, allowance allocation formulas, and enforcement intensity differ across pilots. The

[1] Active programs include the European Union, New Zealand, China, South Korea, Kazakhstan, Switzerland, and 22 local jurisdictions including California and Regional Greenhouse Gas Initiative states. Fifteen additional programs are planned.

variation is not random. Regions with stronger pre-existing environmental governance set more stringent ETS rules ex post. Firms operating in these regions could therefore anticipate ex post stringency from observable ex ante signals, including local environmental enforcement budgets, third-party green ratings, and pollution-fee schedules. The setting provides plausibly exogenous variation in expected policy that we measure with regional indicators and, for listed firms, with firm-level investor relations disclosures.

Our findings reveal a consistent pattern of strategic adaptation. Following the 2011 national announcement of the pilot program, firms in regions where stringent policies are anticipated raise carbon-related patent applications and do not expand emissions. Firms in regions where lenient enforcement is anticipated raise emission levels and emission intensity, consistent with strategically inflating the historical emission baselines that become the basis for allowance allocation. Following actual pilot implementation in 2013 and 2014, the pattern persists. Firms in strong-policy regions reduce both emission levels and intensity and continue to expand decarbonization patenting. Firms in weak-policy regions show no statistically detectable response. A placebo test on non-ETS firms within pilot regions yields null effects, ruling out broad contemporaneous shocks.

Two further pieces of evidence sharpen the strategic interpretation. First, we construct a firm-level measure of expected policy stringency from textual analysis of investor relations management (IRM) transcripts. Listed firms that discuss carbon-market topics more directly and more frequently with investors before the pilots opened are classified into Strong, Middle, and Weak expectation tiers. The pattern observed at the regional level reappears at the firm level. Strong-expectation firms reduce emission intensity and increase decarbonization patents. Weak-expectation firms expand emissions. The IRM measure builds on the firm-level text analysis literature (Hassan et al., 2019; Sautner et al., 2023a) and provides a direct firm-level proxy for expected carbon-policy stringency that complements the regional indicators. Second, we examine the reverse channel. Local governments adjust subsequent policy stringency in response to observed firm actions. Regions with higher lagged carbon-related patenting receive tighter allowance allocations in the following year. Regions with higher lagged emissions receive looser allocations. The two findings together trace out the two-way feedback predicted by Biais and Landier (2022).

The introduction of the national ETS in 2021 provides an out-of-sample test. The national system covers only the power sector and uses a higher inclusion threshold than any regional pilot. Power firms previously regulated under stringent regional pilots therefore face less stringent rules under the national framework. Consistent with strategic adaptation, power firms in weak-policy pilot regions expand emissions after transition, while non-power firms in the same regions cut emissions as local authorities tighten oversight of remaining sectors to offset the power-sector increase.

Our findings contribute to four strands of literature. First, we add to the broad literature on ETS effectiveness. Prior work typically estimates a single average treatment effect of program implementation. We show that this average masks systematic heterogeneity in firm response that is driven by expectations about future stringency, not by formal program launch. Heterogeneity by ex ante expected policy stringency helps explain why aggregate ETS effects appear weak or mixed in cross-country settings. Second, we speak to a growing finance literature on the real effects of climate policy. Bartram et al. (2022) document financial-constraint spillovers from US state-level cap-and-trade rules; Ivanov et al. (2024) show that cap-and-trade exposure raises corporate borrowing costs through the lending channel; Shive and Forster (2020) contrast emission outcomes for public and private firms under uniform pollution rules. These studies take policy stringency as exogenous to firm behavior. We instead show that stringency is itself an equilibrium outcome of firm-regulator interaction, with direct implications for how average treatment effects estimated from a single policy event should be interpreted. Third, we contribute to the literature on China's ETS (Cao et al., 2021; He et al., 2024; Lin and Jia, 2018; Li et al., 2018; Zhu et al., 2019; Weng et al., 2022; Luan et al., 2025). Most prior studies use computational simulations or aggregate sector-level data. We provide firm-level evidence on heterogeneous responses by policy stringency, including from the 2021 national ETS transition. Fourth, and most directly, we provide the first empirical test of strategic complementarity between firms and regulators in the Biais and Landier (2022) sense. The combination of staggered regional pilots with observable proxies for expected stringency and observable downstream policy adjustments allows us to characterize the two-way feedback channel rather than estimate one side of it.

The remainder of the paper is organized as follows. Section 2 provides background on carbon markets in China. Section 3 describes the data and empirical strategy. Section 4 reports the corporate response. Section 5 reports the government response. Section 6 concludes.

2 Background on 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). 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). China's carbon emission markets are now the largest carbon trading markets worldwide. The seven pilot programs operated independently of each other, with discretionary power to set the policy and coverage of carbon allowance allocation.

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. 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 firm i in year t in region k is

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

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

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

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

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

The coefficients $\beta_{CT,k}$ and $\beta_{TPS,k}$ capture the stringency of the carbon allocation policy. A smaller coefficient (either $\beta_{CT,k}$ or $\beta_{TPS,k}$) allocates fewer allowances and indicates a stricter policy in region k. We manually collect the carbon allocation policies in each region and summarize them in Appendix A.

[2] We follow the terminology used by Burtraw et al. (2014), Goulder et al. (2019), Yeh et al. (2021), and Goulder et al. (2023). Some studies refer to CT and TPS as mass-based and rate-based, respectively.

2.2 Coverage

In addition to different carbon allocation policies, pilot regions also varied in their coverage of firms in the regional ETS. In Hubei, industrial firms with more than 40,000 tons of carbon emissions in 2010 or 2011 were included in the 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, indicating a more stringent carbon policy in the region.

2.3 Province-level policy stringency

Regions have discretionary power to establish local carbon policies, so comparing the stringency of policy between regions is important. Carbon policies are usually not disclosed before ETS trades. For example, the carbon allowance coefficients $\beta_{CT,k}$ and $\beta_{TPS,k}$ are not disclosed to firms before carbon trades. As a result, firms have to make carbon emission decisions based on their expectations of carbon policies. After local ETS is implemented, firms know the local carbon policies. From the firm perspective, we therefore employ an ex ante information set to predict future policy stringency before ETS starts, and use the ex post policy disclosed to measure policy stringency after ETS starts.

2.3.1 Ex ante information set

Our ex ante information set contains three measures, including 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 use 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] We classify the first four regions (Beijing, Shenzhen, Guangdong, and Shanghai) as strong regions and the remaining three as weak.

Second, we use local government expenditure on environmental protection in 2009–2011 to measure the intensity of environmental investment by a local government.[4] Guangdong, Beijing, Hubei, and Shenzhen have higher environmental and pollution control budgets than Chongqing, Shanghai, and Tianjin. We classify the first four regions (Beijing, Shenzhen, Guangdong, and Hubei) as strong and the other three as weak.

Third, we use the City Green Development Index Rankings as third-party ratings. The index is 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. The index considers 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 green development are Shenzhen, Haikou, Kunming, Beijing, Hefei, Guangzhou, Dalian, Qingdao, Changsha, and Fuzhou, and there are 19 cities that scored below the average level. We classify Beijing and Shenzhen as strong and the remaining five as weak under this ranking.

We use these three ex ante measures to proxy for firms' expectations about local carbon policies. One concern is whether these three measures could be influenced by firms before ETS announcements (such as pollution fees affected by firm lobbying or evasion). The concern is limited because we aim to examine the incremental effects of ETS on corporate adaptation.

Panel A of Table 1 summarizes these three ex ante measures in Columns (1)–(3), respectively. Column (4) provides a summary classification. We classify a region as strong if it is strict in all of Columns (1)–(3), weak if it is weak in all of Columns (1)–(3), and middle otherwise. Beijing and Shenzhen have strong environmental policies, Chongqing and Tianjin

[3] See Appendix B for details.

[4] See Appendix C for details.

have weak ones, while Shanghai, Guangdong, and Hubei are middle.

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. We can therefore cross-check the policy-stringency measure that uses ex ante information against 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 the local ETS, adopt different thresholds, use different allowance allocation policies (CT or TPS), or impose different CT or TPS coefficients. The power industry, for example, uses CT allocation in Chongqing but TPS allocation in Beijing. Comparing the stringency of policy between regions is therefore challenging. 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. The coverage threshold in Tianjin is 20,000 tons of average carbon emission in 2009–2012, so firms in Tianjin with average carbon emissions greater than 20,000 tons are included in the carbon market. The lower the threshold, the more firms are included and the stricter the policy. We sort all regions by their thresholds and classify a region as strong if its threshold is below the median.

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. A lower coefficient implies less carbon emission allowance and hence a stricter policy. We classify a region as strong if its coefficient is below the median.

We summarize the policy stringency of these three measures (the coverage threshold, CT coefficient, and TPS coefficient) for a region in Columns (1)–(3) of Panel B, Table 1.

A region is classified as strong only if it is strong across all three measures. A region is classified as weak only if it is weak across all three measures. Column (4) of Panel B reports the results. The ex post classification in Panel B agrees with the ex ante classification in Panel A. The agreement is itself a prediction of the rational-expectations equilibrium underlying our empirical design. If firms could not anticipate stringency from ex ante signals, the two classifications would diverge. The agreement validates that ex ante signals were informative about realized policy.

2.4 Firm-level policy stringency

The province-level policy-stringency measure treats every firm in a pilot region as facing the same expected carbon policy. This province-level measure cannot capture variation in expectations across firms in the same region, and a pilot city is typically subject to several overlapping environmental policies that a province-level treatment indicator cannot cleanly separate from the ETS policy-expectation channel. We complement the regional measure with a direct firm-level measure of policy expectation, constructed from each listed firm's own communication with investors before the pilots were implemented. The firm-level measure provides a sharper proxy at the cost of restricting attention to listed firms with sufficient investor-relations coverage, so we treat it as complementary evidence rather than the baseline.

We measure firm-level policy expectations using Investor Relations Management (IRM) records for Chinese A-share-listed firms during the announcement window from 2011 to 2013, drawn from the CSMAR investor-relations activity database (extract of 2026-07-20). Each record is a transcript of an investor meeting that contains investor questions and the firm's responses on operating, financial, and policy-related topics, comparable to an earnings call or investor question-and-answer transcript for a US-listed firm. A firm that discusses the carbon market more often and in more concrete terms is taken to anticipate a stricter carbon policy. IRM disclosures may also reflect a firm's own decarbonization plans, but plans are themselves a function of expectations in our framework, so the IRM-PCA score captures the joint forecast-plan bundle that the strategic-interaction channel operates through. The approach builds on a growing literature using firm-level disclosures to measure exposure to political and climate-related policy (Hassan et al., 2019; Krueger et al., 2020; Sautner et al., 2023a,b; Li et al., 2024).

We construct a keyword dictionary of 97 terms from official ETS policy documents, such as the National Development and Reform Commission notice launching the carbon-trading pilot (NDRC 2011-2601) and the State Council 12^{th} Five-Year Plan, and expand it with co-occurring terms in the IRM transcripts of the treated listed firms. The 97 terms are classified into five groups, ordered by closeness to the pilot ETS, ranging from the most direct policy names in the first group to the broadest corporate-sustainability language in the fifth group. Appendix F reports the full dictionary with the rationale and sources for each term. For a firm i we count the total number of keyword hits in each group across all of its IRM records during the announcement window, yielding a five-dimensional vector of group-specific hit counts $(T1_i, T2_i, T3_i, T4_i, T5_i)$.

Next, we standardize the five group-hit counts across treated firms and apply principal component analysis (PCA) to aggregate them. The firm-level policy-expectation score is each firm's projection onto the first principal component, with the sign normalized so that more direct and more frequent discussion of the carbon market corresponds to a higher score. The first principal component delivers a single data-driven index that summarizes the common variation in carbon-policy attention across the five groups.

Last, we use the PCA score to classify treated firms. Of the 182 treated listed firms, 53 have at least one IRM record in the 2011–2013 announcement window. Within these 53 firms, we assign the top quartile by PCA score, namely the 14 highest-scoring firms, to the Strong group. At the other end, 18 firms have IRM records that contain no carbon-policy keyword at all and are therefore tied at the PCA minimum; these firms never raise the carbon market with investors during the announcement window and form the Weak group.

The remaining 21 firms, which discuss carbon-policy topics but less directly or less frequently than the top quartile, form the Middle group. The rest 129 treated firms with no IRM record during the announcement window form a separate Missing group. Absence of IRM activity may reflect non-disclosure rather than a particular policy expectation, and we keep them in the treatment group for estimation, but do not interpret coefficients from this group.

3 Data and empirical methodology

3.1 Data sources and measures

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 on variable definitions and data sources.

1. **China National Tax Survey Data (CNTSD)**: Panel data at the plant level spanning 2007–2016. Includes detailed accounting information such as employees, total production output, total assets, total liabilities, and production equipment. Also includes environmental metrics including coal, natural gas, and oil consumption; sulfur dioxide (SO_2), nitrogen oxides (NO_x), and wastewater output; 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 NO_x emissions, SO_2 emissions, coal consumption, natural gas consumption, and other related environmental indicators.

3. **Chinese Industrial and Commercial Registered Enterprises Database**: Adds to the CNTSD by providing 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**: Daily trading data for regional carbon markets, including close prices and trading volumes.
- **Carbon Emission Market Company Information**: Annual data on the companies that participate in pilot carbon emission trading schemes. The treatment group in this paper is based on the firms identified in this database.
- **Investor Relations Activity Records**: Investor relations activity records disclosed by Chinese A-share listed firms. Each record contains the meeting date, the participating investors, and the full transcript of the questions and answers exchanged at the firm's investor meeting. We use these records during 2011–2013 to construct the firm-level policy-expectation measure described in Section 2.4.

5. **Incopat Patent Database**: 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. The dataset spans 2019–2023, encompassing the pre- and post-implementation periods of the national carbon market.
7. **The Emissions Database for Global Atmospheric Research (EDGAR)**: City-industry level emissions data spanning 1970–2023.

3.2 Empirical methodology

3.2.1 Difference-in-differences estimation

Our main identification is a difference-in-differences design (De Simone et al., 2024). Firms included in the regional pilot ETS are treated. We study corporate behavior during three stages, before the announcements of pilot regional ETS, after the announcements but before implementation, and after implementation. There are two treatments, namely the announcement and the implementation. We use three treatment dummies, Strong, Middle, and Weak, to indicate strong, middle, and weak environmental policies in a region, respectively. We use the ex ante measure to classify these seven regions before the announcements and the ex post measure to classify them after implementation.

Identification rests on a timing argument. At the 2011 announcement, only ex ante signals about future stringency are available to firms, because allowance rules are disclosed only at implementation in 2013–2014. The announcement effect therefore captures the response to anticipated stringency, separately from any response to realized policy.

Because the seven regional pilots start their emission trading schemes in different years, the implementation treatment is adopted in a staggered fashion. To accommodate this staggered adoption and the possibility that treatment effects are heterogeneous across cohorts and over time, we estimate the treatment effects with the staggered difference-in-differences estimator of Callaway and Sant'Anna (2021) (CSDiD). The estimator first computes group-time average treatment effects, comparing each treated cohort only with the not-yet-treated and never-treated firms over the same calendar period, and then aggregates these effects into an overall average treatment effect on the treated. We apply this estimator to both the announcement effect and the implementation effect so that the two sets of results are produced within a single consistent estimation framework.

Under treatment-effect heterogeneity, the conventional two-way fixed-effects (TWFE) estimator can be biased because it implicitly places negative weights on certain treatment-effect comparisons when later-treated units serve as controls for earlier-treated units (Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2024). The Callaway-Sant'Anna estimator addresses this concern. The econometric specification is as follows:

$$y_{i,t} = \beta_1 Strong_i \times Post_t + \beta_2 Middle_i \times Post_t + \beta_3 Weak_i \times Post_t + \epsilon_{i,t}, \tag{3}$$

where $y_{i,t}$ is the outcome variable for firm i in year t; $Strong_i$, $Middle_i$, and $Weak_i$ are dummy variables equal to one if the policy expectation of firm i is measured as strong, middle, or weak, respectively, and zero otherwise; $Post_t$ is a dummy variable that equals one for the years when or after the treatment occurs and zero otherwise; and $\epsilon_{i,t}$ is the error term. We are interested in the impacts on carbon emission, carbon emission intensity, production, and the number of decarbonization-related patents. β_1, β_2, and β_3 show the average treatment effects of ETS announcement or implementation on firms under different policy stringency, estimated with the Callaway and Sant'Anna (2021) estimator.

Equation (3) does not include firm or year fixed effects explicitly because they are absorbed by the Callaway and Sant'Anna (2021) estimator by construction. The estimator constructs each group-time average treatment effect from the change in the outcome of a treated cohort relative to a clean control group between the same two periods, so any time-invariant firm characteristic and any shock common to all firms in a given year are differenced out automatically. Statistical inference is based on the wild cluster bootstrap, with clusters defined at the firm level.

For the announcement effect, the treatment timing is common to all pilots (the 2011 announcement), so the treatment is not staggered and the conventional TWFE estimator is also valid. In this single-cohort case, the CSDiD estimator coincides mechanically with a standard 2-period DiD comparing pre-announcement and post-announcement outcomes for treated and matched control firms. We choose CSDiD for both announcement and implementation effects so that their coefficients sit on the same scale with the same interpretations. As a robustness check, we re-estimate the announcement effect with the standard TWFE and obtain consistent results. Last, we also run a standard triple DiD on the matched sample and report it in the Appendix J.

$$
\begin{aligned}
y_{i,t} = {} & \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Strong_i \\
& + \beta_4 (Treatment_i \times Post_t) + \beta_5 (Treatment_i \times Strong_i) + \beta_6 (Post_t \times Strong_i) \\
& + \beta_7 (Treatment_i \times Post_t \times Strong_i) + \eta_i + \sigma_t + \epsilon_{i,t},
\end{aligned} \tag{4}
$$

where $Treatment_i$ equals one if firm i is enrolled in the pilot ETS; $Strong_i$ equals one for treated firms in strong-policy regions and their matched controls; η_i and σ_t are firm and year fixed effects; and the remaining terms are as in Equation (3). Because η_i and σ_t absorb all time-invariant firm characteristics and all common-year shocks, the firm-level constants $Treatment_i$, $Strong_i$, and $Treatment_i \times Strong_i$ are absorbed by η_i, and the year-level indicator $Post_t$ is absorbed by σ_t; only β_4, β_6, and β_7 are estimated. The coefficient β_7 identifies the differential treatment effect in strong-policy regions relative to non-strong (weak or middle) regions, and standard errors are clustered at the industry level.

3.2.2 Matched sample

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. The emission level and the size of the treatment group are usually larger than those of the untreated firms from the same region. We therefore cannot use treated and untreated firms from the same pilot region as matched samples. Variations between regions 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 propensity score matching (PSM).[5] For each treated firm, we first find firms from the non-pilot neighborhood regions and within the same sector. We then consider their carbon emissions and firm production in 2009 and 2010 (two years before the ETS announcement) and select 5 untreated firms as the matched sample. Figure 1 plots the geographical distribu-

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

tion of the treated firms and the matched firms. The matched sample defines the treatment and control groups used by the staggered difference-in-differences estimator.

3.3 Summary statistics

Table 2 reports the summary statistics for the matched samples. All variables are in logarithmic values. Comparing the treated and matched firms, treated firms have larger production, higher carbon emission (in levels and intensity), and more carbon-related patents.

4 Corporate responses to carbon policies

4.1 Announcement effects of regional ETS

We first estimate the announcement effects of the regional pilot ETS markets with the staggered difference-in-differences estimator of Section 3.2.1, applied to Equation (3). The treatment is the announcement 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 stringency to differentiate the seven pilot regions, namely Panel A of Table 1.

Table 3 reports the regression results. Compared with untreated firms, treated firms do not reduce production, as shown in Column (3). Production rises, especially for treated firms 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 does not hinder economic growth or firm performance. Columns (1)–(2) show that treated firms in regions with middle or weak environmental policies actually increase carbon emissions, at both levels (about 0.36σ and 0.29σ respectively) and emission intensity (about 0.30σ and 0.36σ respectively), measured in standard deviations of the treated subsample reported in Table 2. The pattern is consistent with firms strategically signaling a high emission status in order to gain advantage (such as receiving more carbon allowances) during the implementation stage of the local ETS. Column (4) shows that treated firms in regions with strong environmental policies increase their carbon-related patents, indicating that these firms invest more in decarbonization technology. We do not see comparable impacts on green innovation for firms in regions with weak policies.

Figure 2 compares the time series of carbon-related patents for treated firms in regions with strong and weak environmental policies. The graph computes the average number of patents related to decarbonization for treated firms and subtracts that of matched firms from non-pilot regions. The model-free mean plot shows a clear pattern that firms expecting strong environmental policies invest more in decarbonization technology. Zhu et al. (2019) and Weng et al. (2022) show that ETS promotes green innovation. Our evidence shows that this effect is concentrated in regions with strong environmental policies.

The same specification estimated by the conventional TWFE difference-in-differences regression on the matched sample, reported in Appendix Table I.17, yields qualitatively similar results, consistent with the CSDiD estimates.

For further robustness, we perform a standard triple DiD test in Appendix J and Table J.18, comparing the announcement effects in regions with strong and non-strong (weak or middle) environmental policies. The results are qualitatively similar to those in Table 3. Treated firms in regions with non-strong environmental policies strategically increase carbon emissions after the announcement of pilot ETS, while strong environmental policies induce firms to invest more in carbon-related technology.

4.2 Implementation effects of regional ETS

We next estimate the implementation effects of local ETS markets with the same staggered difference-in-differences estimator, applied to Equation (3). The treatment is the implementation of a local ETS market. Since carbon policies are now disclosed to companies, we use the ex post measure of stringency of carbon policies to differentiate the seven pilot regions, see Panel B of Table 1.

This classification of stringency 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, the average annual carbon prices in regions with strong carbon policies are consistently higher than those in regions with weak carbon policies.

Table 4 reports the panel regression results from the matched sample. Both the emission level (Column (1)) and the emission intensity (Column (2)) decrease for treated firms in regions with strong carbon policies, by about 0.43σ and 0.30σ respectively in standard deviations of the treated subsample reported in Table 2. There are no significant impacts on firms in regions with middle or weak carbon policies. Column (4) shows that ETS has a significant positive impact on carbon-related patents for firms in regions with strong carbon policies.

For robustness, we perform a standard triple DiD test in Appendix J. Table J.19 presents the implementation effects in regions with strong and non-strong (weak or middle) environmental policies. Treated firms in regions with strong environmental policies reduce levels and intensity of carbon emission after implementing a pilot ETS, qualitatively similar to those reported in Table 4.

4.3 Parallel trends

The Callaway-Sant'Anna estimator relies on a conditional parallel-trends assumption between treated and never-treated firms. We assess this assumption directly by examining the time path of each outcome variable around the two treatment events, the 2011 announcement and the 2013–2014 implementation. Figures 4, 5, and 6 plot the mean carbon emission, emission intensity, and carbon-related patents for treated firms (relative to matched controls) in regions with strong, middle, and weak environmental policies. Years on the horizontal axis are normalized so that the 2011 announcement is year zero and the 2013–2014 implementation is year two.

Two patterns are visible. Before the announcement, the three policy-strength groups track each other closely and show no systematic divergence relative to their matched controls. The pre-treatment trends are flat and economically small for emissions, emission intensity, and patents. After the announcement, the groups separate in the directions predicted by the strategic story. Emissions and emission intensity rise for treated firms in weak and middle regions and stay flat or fall in strong regions. Carbon-related patents accelerate sharply for firms in strong regions and stay close to the control mean elsewhere. The separation widens after implementation in year two. The absence of pre-trend divergence supports the identifying assumption, and the post-treatment pattern matches the regression evidence.

4.4 Heterogeneity by firm influence over local governments

The strategic interpretation predicts that firms with more political and economic leverage over local governments should respond differently to anticipated policy. Firms that expect to influence policy design can game emission baselines more aggressively during the announcement phase. We examine this prediction directly. Using the China National Tax Survey Data, we proxy a firm's local influence by its tax contribution to the local government. Influential firms are the top 40% taxpayers in a region, and the rest are classified as non-influential. We re-estimate the announcement and implementation effects with the same staggered difference-in-differences estimator separately for the two subsamples, applying the same PSM procedure, and evaluate (i) announcement effects using the ex ante measures of policy stringency and (ii) implementation effects using the ex post measures.

Table 5 reports announcement effects in Panel A and implementation effects in Panel B. During the announcement period (Panel A), influential firms exhibit a broader and stronger response than non-influential firms across all three policy regimes. In Strong-expectation regions, influential firms significantly cut carbon emissions (Column (1)) and significantly raise production (Column (5)) and carbon patents (Column (7)), while non-influential firms only raise patents (Column (8)) and show no statistically detectable change in emissions, intensity, or production. In Middle-expectation regions, influential firms significantly expand both the level and intensity of emissions (Columns (1) and (3)) and significantly increase carbon patents (Column (7)); non-influential firms show a marginally significant rise in emissions (Column (2)), but no significant change in intensity or patents. In Weak-expectation regions, influential firms significantly increase emissions and emission intensity (Columns (1) and (3)), while non-influential firms show no statistically significant change in any of the four outcomes. The pattern is consistent with the strategic interpretation in which firms with more political and economic leverage game emission baselines more aggressively ahead of the implementation phase, particularly when they anticipate a weak or moderate enforcement environment.

During the implementation period (Panel B), the two groups respond similarly. In Strong-expectation regions, both influential and non-influential firms significantly reduce carbon emissions and emission intensity and significantly raise production and carbon patents (Columns (1)–(8)). Influential firms show larger point estimates on emissions and intensity (-2.09 and -2.05) than non-influential firms (-1.18 and -2.00). In middle-expectation regions, neither group shows a statistically detectable response across the four outcomes. In weak-expectation regions, influential firms show no significant change in emission level or intensity, while non-influential firms continue to significantly raise emissions (Column (2), $+1.29$), suggesting that strategic baseline inflation persists into the implementation phase for firms with limited monitoring exposure. Compared with the clear gap in the announcement period, the implementation responses are qualitatively closer between influential and non-influential firms in strong-policy regions but diverge in weak-policy regions along the emission-expansion margin.

4.5 Placebo test

To 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. One challenge is that non-ETS firms might respond to the implementation 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. First, we select firms that operate in non-ETS industries but are located in pilot regions. Second, we choose firms with carbon emissions below 25% of the region-specific coverage threshold for the carbon market. Since the coverage threshold in Beijing is 10,000 tons of CO_2, for example, we use firms with annual emissions below 2,500 tons as the placebo pool in Beijing. Third, we further refine the placebo group using propensity score matching so that placebo firms are closely comparable to the treated firms. For each treated firm, we match a placebo firm 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 with the same staggered difference-in-differences estimator on the matched sample of Section 3.2.2. Table 6 reports the DiD estimation results. There are no statistically significant responses of carbon emission level, emission intensity, and carbon related patents 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.

4.6 Firm-level policy expectations from IRM evidence

The province-level analysis in Section 4.1 carries the main identification for the announcement effect. We complement it with a firm-level robustness check that uses the IRM-based policy-expectation measure constructed in Section 2.4. The firm-level check is not a substitute for the baseline. Its purpose is to add within-region variation in expected policy and to address concerns specific to the province-level design. IRM coverage during the announcement window is limited to 53 of the 182 treated listed firms, so the firm-level sample is substantially smaller than the baseline.

We first check whether the IRM-covered and non-covered subsamples among the 182 treated listed firms differ on observables. Appendix Table G.14 compares the two groups on log assets, log production, log carbon emission, and log carbon emission intensity, aggregated to the parent listed firm from the underlying subsidiary panel and averaged over the 2007–2013 window. IRM-covered firms are marginally smaller on log assets ($t = 1.67$), with no statistically detectable difference in production, emissions, or emission intensity. The comparison suggests that IRM disclosure during the announcement window tilts toward somewhat smaller listed firms, but does not pre-select firms with systematically higher or lower carbon footprint.

The subsidiary-level structure of our data also allows us to control for city×year fixed effects, which absorb any time-varying shock common to all firms in the same city and year. This is important because three large city-targeted environmental policies overlap with the ETS pilots in space and time: the National Energy Demonstration City Project (NEDCP, 2014–), the Central Environmental Inspections (CEI, 2015–2018), and the Low Carbon City Pilot (LCCP, 2010–). All three are designated at the city level rather than at the province level, and within a single pilot province some cities are covered while others are not. A province×year fixed effect would conflate these city-level confounders with the ETS announcement, but a city×year fixed effect absorbs them.

Beyond these overlapping policies, the within-region IRM variation addresses a broader identification concern. The province-level ex ante signals, namely pollution fees and environmental budgets, may proxy for unobserved regional fundamentals, such as local governance quality or industrial composition, that drive firm behavior directly rather than through ETS expectations. Because the IRM-PCA group varies across firms within the same pilot region, and city×year fixed effects absorb time-varying city-level shocks, the strategic-expectation channel is identified from cross-firm variation in policy attention rather than from cross-region variation in environmental fundamentals.

We estimate this firm-level specification with the Callaway and Sant'Anna (2021) staggered difference-in-differences estimator at the subsidiary level on the PSM-matched panel of Section 3.2.2, with city×year fixed effects and wild cluster bootstrap standard errors clustered at the firm level, replacing the province-based policy-stringency classification with the firm-level expectation groups.

Table 7 reports the results. The pattern is broadly consistent with the province-level findings in Table 3. Treated firms in the Strong expectation group significantly reduce carbon emission intensity, increase production, and increase carbon-related patents, with a marginally negative point estimate on the emission level. Treated firms in the Weak expectation group instead significantly increase both the level and the intensity of carbon emissions, with no statistically detectable effect on production or carbon-related patents. Treated firms in the Middle expectation group show no statistically detectable change in any of the four outcomes. The expectation-group results therefore confirm the qualitative split between strong-expectation and weak-expectation firms, with the Middle group sitting between the two and showing no distinct response of its own.

The group-based test uses only the ordinal split of firms into Strong, Middle, and Weak expectation groups, discarding the within-group variation in the underlying IRM-PCA score. We exploit this continuous variation as a complementary check. For each firm-year in 2011–2013, we regress the four corporate outcomes on the firm-year IRM PC1 score and the same lagged size controls:

$$y_{i,t} = \alpha + \beta\,\mathrm{IRM\ PC1}_{i,t} + \gamma_1 \log(\mathrm{Asset})_{i,t-1} + \gamma_2 \log(\mathrm{Liability})_{i,t-1} + \varepsilon_{i,t}, \tag{5}$$

where IRM $\mathrm{PC1}_{i,t}$ is the first principal component of the z-scored T1–T5 carbon-keyword hit counts on the parent listed firm's IRM Q&A text in year t, jointly estimated across treated and non-treated firms, with IRM PC1 $= 0$ assigned to firm-years with no carbon talk; standard errors are clustered at the listed-firm (parent) level. We estimate Equation (5) separately on the ETS-treated and non-treated subsidiary samples in our matched panel.

Appendix Table H.15 reports the results. Among ETS-treated subsidiaries (Panel A), a higher IRM PC1 score is associated with significantly lower carbon emission and lower carbon emission intensity, both at the 5% level. Because the PC1 sign is normalized so that more direct carbon-policy discussion corresponds to a higher score, weaker policy expectation (lower PC1) translates into higher emission level and intensity, consistent with the strategic-expansion result in the group-based DiD. The placebo regression on non-treated subsidiaries (Panel B) finds no statistically significant association on either emission or intensity, indicating that the relationship in Panel A is specific to firms exposed to the pilot ETS rather than a general feature of listed-firm disclosure. To address inference concerns in the small 25-observation treated cell, Appendix Table H.16 re-estimates Equation (5) with randomization inference, block-permuting each listed parent's whole-history PC1 trajectory; the IRM PC1 coefficient on emission and emission intensity remains significant at the 10% level under exact RI p-values.

Across the group-based DiD and the continuous-score OLS, firms with stronger carbon-policy expectations reduce emissions and invest in decarbonization, while firms with weaker expectations expand emissions ahead of implementation.

4.7 TPS vs. CT allocation policies

We next ask whether carbon allowance allocation policies (TPS or CT) matter for corporate behavior. Allocation-design choices have first-order real-effects implications under cap-and-trade, including spillovers to firm financing (Ivanov et al., 2024; Bartram et al., 2022).

A central difficulty is that carbon allowance allocation policies may be chosen endogenously, given the strategic interaction between local governments and firms. Pilot regions endogenously chose TPS or CT for certain industries. We use instrumental variables to address this endogeneity. To implement TPS, local governments need information on firm production, so the availability of production information is critical for the choice between TPS and CT. Such information may not be available for several reasons. Firms, especially non-public firms, may not be required to disclose their production information. Firms often have strong incentives to hide production information for tax avoidance purposes. Local governments in China rely on reports from the National Bureau of Statistics to collect information about firm production. The National Bureau of Statistics requires companies above the designated size to report their production. During 2007–2010, the designated size was RMB 5 million, so local governments have production information for firms above RMB 5 million. Firms with size greater than RMB 5 million are therefore more applicable to TPS. The threshold is decided by the central government, so it is exogenous to firm behavior. 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

$$TPS_{i,t} = \gamma_1 \mathbf{I}_{i,t,5m} + Controls_{i,t} + \epsilon_{i,t}, \tag{6}$$

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

$$y_{i,t} = \beta_1 \widehat{TPS}_{i,t} \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \varepsilon_{i,t}, \tag{7}$$

where $y_{i,t}$ is the outcome variable of interest 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; and $\varepsilon_{i,t}$ is the error term. β_1 shows the average treatment effects of TPS on corporate behavior. For firms under CT, we run similar instrumental variable regressions, replacing TPS in Equations (6) and (7) by CT.

Appendix Table E.12 reports the first-stage results. 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. Only the threshold of RMB 5 million is statistically significant at the 10% level. This validates our instrumental variable.

Table 8 reports the second-stage results. Panel A reports the TPS estimates and Panel B reports the CT estimates. In regions with strong carbon policies, both designs significantly reduce the carbon emission level (Column (1)) and emission intensity (Column (2)) and significantly increase carbon-related patents (Column (4)). In regions with middle carbon policies, TPS continues to significantly reduce both the level and intensity of emissions, but the carbon-patent effect is not statistically significant; under CT, none of the four outcomes is significant. In regions with weak carbon policies, neither design produces a detectable change in emissions or patents. The stringency of the carbon policy therefore matters more than the choice of allocation design. Imposing a strict carbon policy, under either rule, is necessary to achieve carbon reductions and promote carbon-related innovation.

4.8 Implementation effects of national ETS

In 2021, China launched its national carbon emissions trading scheme (ETS), covering 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 may induce heterogeneous effects on carbon emissions for firms in different regions and industries. While power industry firms have been integrated into the national ETS, other carbon-intensive industries remain under regional market jurisdiction (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, may affect the carbon emission of non-power industries in the regional carbon markets.

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 the national ETS on non-power industries 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:

$$Emission_{i,t} = \beta_1 PilotRegion_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{8}$$

where $Emission_{i,t}$ is the logarithm of 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; and $\epsilon_{i,t}$ is the error term.

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

$$Emission_{i,t} = \beta_1 Strong_i \times Post_t + \beta_2 Middle_i \times Post_t + \beta_3 Weak_i \times Post_t + \beta_4 \eta_i + \beta_5 \sigma_t + \epsilon_{i,t}, \tag{9}$$

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

Table 9 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 the increase is mainly driven by firms in pilot regions with weak policy stringency. The national ETS extends coverage to power firms in all regions but imposes lower stringency than the pilots, 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. 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 extend the 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 (8) and (9), 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 EDGAR. 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. 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 tons of CO_2 in Chongqing.

5 Government responses to corporate actions

The corporate evidence so far establishes one side of the strategic interaction. Firms with stronger expectations of policy stringency invest in decarbonization, and firms with weaker expectations expand emissions. The two-way feedback predicted by Biais and Landier (2022) requires that local regulators in turn adjust stringency after observing firm actions. We now examine this reverse channel directly. The regulator-response side connects to work on how policy makers update environmental market design from observed market and firm-level signals (Meng, 2017; Borenstein et al., 2019).

We estimate

$$PolicyStringency_{i,t} = \beta\ CorporateAction_{i,t-1} + \gamma\ Controls_{i,t-1} + \varepsilon_{i,t}, \tag{10}$$

where $PolicyStringency_{i,t}$ represents the stringency of the carbon policy set by region i at the implementation stage in year t; $CorporateAction_{i,t-1}$ denotes the corporate carbon actions in region i in year $t-1$; and $Controls_{i,t-1}$ is a set of control variables that could affect carbon policies, including local GDP and other pollution fees charged. We measure the corporate carbon actions of firms participating in the carbon markets in three ways, including carbon patents, the carbon emission level, and the carbon emission intensity. The independent variables are lagged by one year to capture the decision-making process of local governments. Because the policy stringency is observed only after a regional ETS is implemented, the lagged corporate actions in the first implementation year are those taken during the announcement period, whereas in the subsequent years they are those taken during the implementation period. In 2013, the first year of implementation in Shanghai, the corporate action variables equal their 2012 values, so that the estimates for the first year capture the government's response to firms' actions during the announcement period, while the estimates for the later years capture its response to firms' actions during the implementation period. The lag structure also mitigates simultaneity concerns. Allowance allocation parameters are set in a discrete annual process before the compliance year begins, so within-year reverse causality from contemporaneous regulatory decisions to lagged corporate actions is implausible.

In Panel A of Table 10, we use the average carbon allowance per firm to measure the stringency of carbon policies, calculated as the total carbon allowances divided by the total number of firms participating in the carbon markets. We take the natural logarithm of this measure as the dependent variable. The average allowance per firm 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 (lower carbon allowance). Columns (2) and (3) indicate an insignificant coefficient of lagged carbon emission or carbon emission intensity.

We next examine the TPS or CT allocation policies 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 10, respectively. A lower TPS or CT coefficient represents more stringent carbon policies. Higher carbon-related patents in the previous year lead to more stringent carbon policies, namely a lower TPS coefficient in Column (4) and a lower CT coefficient in Column (7). Higher carbon emission or carbon emission intensity leads to less stringent carbon policies, namely a higher TPS coefficient in Columns (5) and (6), or a higher CT coefficient in Column (8).

Combining these results with the announcement-effect evidence in Section 4.1 traces out the strategic baseline inflation channel under both allocation designs. Under CT, allowance is calculated as historical emissions multiplied by a CT coefficient (Equation (1)), so the announcement-window emission increases in weak-policy regions translate mechanically into larger CT allocations at implementation. The positive coefficient on lagged emissions in Column (8) compounds this effect, because regulators in regions where firms emitted more also set a looser $\beta_{CT,k}$. Under TPS, allowance is calculated as production multiplied by a

TPS coefficient $\beta_{TPS,k}$ (Equation (2)), which is similar to emission intensity. The positive coefficient on lagged emission intensity in Column (6) shows that regulators in regions where firms emitted more set a looser $\beta_{TPS,k}$, so the firm-level emission inflation still translates into larger allocations through the regulator's discretion. Both allocation designs therefore reward the strategic emission increases documented in Section 4.1, either directly through the historical-emission baseline (CT) or indirectly through the historical-emission intensity (TPS).

Table 10 reveals a consistent pattern across allocation policies. Local governments adjust the stringency of the carbon policy in response to corporate actions. Combined with the corporate evidence in Section 4, the result traces out the two-way feedback predicted by Biais and Landier (2022). Firms in regions where stringent policies are anticipated invest in decarbonization, and regulators who observe this investment ratify the firms' expectations by setting tighter allowance allocations.

5.1 Placebo test using non-pilot neighbour provinces

One concern with the baseline government-response result is that pilot-province policy stringency might track a broader regional green-economy trend rather than the actions of pilot-regulated firms in particular. If so, corporate actions from firms in non-pilot regions, which cannot mechanically be the target of pilot policy design, should also appear to predict pilot-province policy stringency. We construct this placebo directly.

For each pilot region we select three non-pilot provinces drawn from the pilot's direct geographical adjacency list, with each pilot assigned a unique three-province set so that no two pilots share an identical triplet.[7] For each pilot year, we replace the corporate-action variable in equation (10) with the mean of the same firm-level outcome (carbon patent,

[7] The neighbor provinces selected for each pilot are as follows. For Beijing, we use Inner Mongolia, Shanxi, and Henan. For Tianjin, we use Inner Mongolia, Shandong, and Hebei. For Shanghai, we use Shandong, Jiangxi, and Fujian. For Chongqing, we use Yunnan, Hunan, and Guizhou. For Guangdong, we use Yunnan, Hainan, and Guizhou. For Shenzhen, we use Jiangxi, Hunan, and Fujian. For Hubei, we use Jiangxi, Henan, and Hunan.

carbon emission, or carbon emission intensity) computed across the pilot's three neighbor provinces, lagged by one year.

Table 11 reports the placebo estimates. None of the nine corporate-action cells is statistically significant at conventional levels. The control variables retain the same sign and significance pattern as in the main government-response table. The absence of a placebo effect indicates that the relationship documented in Table 10 is specific to actions taken by firms inside the pilot region, rather than reflecting a broader contemporaneous trend that happens to correlate with pilot-province policy stringency.

5.2 Government response to firm-level policy expectation

The corporate-action measure used in Table 10 is observable to the regulator only after it has been realized. A sharper test of the strategic-feedback channel is whether regulators respond to firms' ex ante policy expectation, which is formed before any allowance is set. We use the firm-level IRM policy-expectation classification of Section 2.4 as this ex ante signal.

We extend the classification logic to the full universe of A-share listed firms. The same Chinese carbon-policy keyword dictionary (Appendix F) and the same PCA group-construction rule are applied to all 5,004 A-share listed firms with IRM disclosure during 2011–2013. Each firm is assigned to the Strong ("strict") group if it falls in the top quartile of the IRM-PCA score, mirroring the construction at the treated-firm sample in Section 2.4. We then aggregate to the province-year level: for each province p and year t, $\text{NStrict}_{p,t}$ is the count of listed firms with headquarters in p that are classified into the Strong group. Province of a listed firm is taken from the CSMAR `TRD_Co` listing of registered office, with Shenzhen treated as an independent pilot region. Listed firms enter the province-year aggregation only from their listing year onward, so that the measure reflects the firms actually visible to the local regulator. The sample is restricted to year ≥ 2013, matching the post-implementation window in which the dependent variables (Allowance per firm, TPS coefficient, CT coefficient) are observed.

We then re-estimate equation (10) with $\text{NStrict}_{p,t}$ replacing the corporate-action variable. Table 12 reports the results. The coefficient on $\text{NStrict}_{p,t}$ is significantly negative for the Allowance per firm (Column 1, -1.173, $p<0.01$), the TPS coefficient (Column 2, -0.662, $p<0.01$), and the CT coefficient (Column 3, -0.021, $p<0.01$). A higher count of Strong-expectation listed firms in a province is therefore associated with a more stringent eventual allowance design across all three measures.

The pattern delivers the firm-to-government leg of the strategic-feedback channel directly. When more listed firms in a province discuss carbon policy intensively in their pre-implementation investor-relations records and therefore signal a strong policy expectation, the local government in turn sets a more stringent allowance allocation when implementation begins. Combined with the corporate-response evidence in Section 4 and the realized-action results in Table 10, this completes the two-way feedback predicted by Biais and Landier (2022): regulators do not act on realized abatement alone, but also on the firms' anticipatory disclosure.

6 Conclusion

Carbon emission trading systems are not designed and implemented in isolation. They evolve through repeated interaction between firms that anticipate future stringency and regulators that adjust stringency after observing firm actions. We document this two-way feedback in the seven Chinese regional ETS pilots and the subsequent national ETS.

Firms in regions where stringent policies are anticipated reduce emissions and invest in decarbonization technology. Firms in regions where lenient enforcement is anticipated expand emissions, consistent with strategic accumulation of the historical emission baselines used to allocate future allowances. Local governments respond by tightening allowance allocations where firms innovate more and loosening them where firms emit more. The pattern is robust to the choice between cap-and-trade and tradable performance standards allocation designs, and to a firm-level expectation measure constructed from investor relations transcripts. Heterogeneous corporate responses by firm political-economic influence reinforce the strategic interpretation. Influential firms game emission baselines more aggressively when policy expectations are weak, while strict enforcement neutralizes firm influence.

The findings have direct policy implications. A discretionary feedback loop between firms and regulators can weaken policy stringency, as firms minimize abatement effort in regions where regulators are anticipated to ratify lenient policy. Mechanisms that commit regulators to a pre-specified stringency pathway, that limit firm influence over local allocation parameters, or that improve transparency about future allowance plans can prevent the strategic ratcheting we document.

References

Bartram, S. M., Hou, K., Kim, S., 2022. Real effects of climate policy: Financial constraints and spillovers. Journal of Financial Economics 143, 668–696.

Bayer, P., Aklin, M., 2020. The European Union emissions trading system reduced CO_2 emissions despite low prices. Proceedings of the National Academy of Sciences 117, 8804–8812.

Biais, B., Landier, A., 2022. Emission caps and investment in green technologies. Available at SSRN 4100087 .

Borenstein, S., Bushnell, J., Wolak, F. A., Zaragoza-Watkins, M., 2019. Expecting the unexpected: Emissions uncertainty and environmental market design. American Economic Review 109, 3953–77.

Borusyak, K., Jaravel, X., Spiess, J., 2024. Revisiting event-study designs: Robust and efficient estimation. Review of Economic Studies 91, 3253–3285.

Burtraw, D., Linn, J., Palmer, K., Paul, A., 2014. The costs and consequences of clean air act regulation of CO_2 from power plants. American Economic Review 104, 557–562.

Calel, R., Dechezleprêtre, A., 2016. Environmental policy and directed technological change: Evidence from the european carbon market. Review of Economics and Statistics 98, 173–191.

Callaway, B., Sant'Anna, P. H., 2021. Difference-in-differences with multiple time periods. Journal of Econometrics 225, 200–230.

Cao, J., Ho, M. S., Ma, R., Teng, F., 2021. When carbon emission trading meets a regulated industry: Evidence from the electricity sector of China. Journal of Public Economics 200, 104470.

Cicala, S., 2015. When does regulation distort costs? Lessons from fuel procurement in us electricity generation. American Economic Review 105, 411–444.

Cui, J., Wang, C., Zhang, J., Zheng, Y., 2021. The effectiveness of China's regional carbon market pilots in reducing firm emissions. Proceedings of the National Academy of Sciences 118, e2109912118.

De Simone, R., Naaraayanan, S. L., Sachdeva, K., 2024. Opening the brown box: Production responses to environmental regulation. Available at SSRN .

Dehejia, R. H., Wahba, S., 2002. Propensity score-matching methods for nonexperimental causal studies. Review of Economics and statistics 84, 151–161.

Fan, Y., Wu, J., Xia, Y., Liu, J.-Y., 2016. How will a nationwide carbon market affect regional economies and efficiency of CO_2 emission reduction in China? China Economic Review 38, 151–166.

Fowlie, M., Reguant, M., Ryan, S. P., 2016. Market-based emissions regulation and industry dynamics. Journal of Political Economy 124, 249–302.

Goodman-Bacon, A., 2021. Difference-in-differences with variation in treatment timing. Journal of Econometrics 225, 254–277.

Goulder, L. H., Long, X., Lu, J., Morgenstern, R. D., 2019. China's unconventional nationwide CO_2 emissions trading system: The wide-ranging impacts of an implicit output subsidy. National Bureau of Economic Research Working Paper 26537.

Goulder, L. H., Long, X., Qu, C., Zhang, D., 2023. China's nationwide CO_2 emissions trading system: A general equilibrium assessment. National Bureau of Economic Research Working Paper 31809.

Hassan, T. A., Hollander, S., van Lent, L., Tahoun, A., 2019. Firm-level political risk: Measurement and effects. Quarterly Journal of Economics 134, 2135–2202.

He, G., Wu, L., Zhang, N., Zhou, Y., 2024. Carbon market with chinese characteristics.

Ivanov, I. T., Kruttli, M. S., Watugala, S. W., 2024. Banking on carbon: Corporate lending and cap-and-trade policy. Review of Financial Studies 37, 1640–1684.

Kantor, D., 2012. Mahapick: Stata module to select matching observations based on a Mahalanobis distance measure, Boston College Department of Economics.

Krueger, P., Sautner, Z., Starks, L. T., 2020. The importance of climate risks for institutional investors. Review of Financial Studies 33, 1067–1111.

Li, M., Zhang, D., Li, C.-T., Mulvaney, K. M., Selin, N. E., Karplus, V. J., 2018. Air quality co-benefits of carbon pricing in China. Nature Climate Change 8, 398–403.

Li, Q., Shan, H., Tang, Y., Yao, V., 2024. Corporate climate risk: Measurements and responses. Review of Financial Studies 37, 1778–1830.

Lin, B., Jia, Z., 2018. Impact of quota decline scheme of emission trading in China: A dynamic recursive CGE model. Energy 149, 190–203.

Liu, Y., Tan, X.-J., Yu, Y., Qi, S.-Z., 2017. Assessment of impacts of Hubei pilot emission trading schemes in China–A CGE-analysis using TermCO2 model. Applied Energy 189, 762–769.

Luan, L., Liu, P., Mei, Y., 2025. The impact of pilot carbon market on firms' performance in China. Energy Economics 142, 108164.

Martinsson, G., Strömberg, P., Sajtos, L., Thomann, C. J., 2022. Carbon pricing and firm-level CO_2 abatement: Evidence from a quarter of a century-long panel, European Corporate Governance Institute–Finance Working Paper.

Meng, K. C., 2017. Using a free permit rule to forecast the marginal abatement cost of proposed climate policy. American Economic Review 107, 748–84.

Ministry of Ecology and Environment, 2024. Progress report of China's national carbon market (2024). Tech. rep.

Sautner, Z., van Lent, L., Vilkov, G., Zhang, R., 2023a. Firm-level climate change exposure. Journal of Finance 78, 1449–1498.

Sautner, Z., Van Lent, L., Vilkov, G., Zhang, R., 2023b. Pricing climate change exposure. Management Science 69, 7540–7561.

Shive, S. A., Forster, M. M., 2020. Corporate governance and pollution externalities of public and private firms. Review of Financial Studies 33, 1296–1330.

Stechemesser, A., Koch, N., Mark, E., Dilger, E., Klösel, P., Menicacci, L., Nachtigall, D., Pretis, F., Ritter, N., Schwarz, M., Vossen, H., Wenzel, A., 2024. Climate policies that achieved major emission reductions: Global evidence from two decades. Science 385, 884–892.

Sun, L., Abraham, S., 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics 225, 175–199.

Weng, Z., Ma, Z., Xie, Y., Cheng, C., 2022. Effect of China's carbon market on the promotion of green technological innovation. Journal of Cleaner Production 373, 133820.

World Bank, 2024. State and trends of carbon pricing dashboard. `https://carbonpricingdashboard.worldbank.org/about#download-data`, accessed: 2025-02-03.

Yeh, S., Burtraw, D., Sterner, T., Greene, D., 2021. Tradable performance standards in the transportation sector. Energy Economics 102, 105490.

Zhu, J., Fan, Y., Deng, X., Xue, L., 2019. Low-carbon innovation induced by emissions trading in China. Nature Communications 10, 4088.

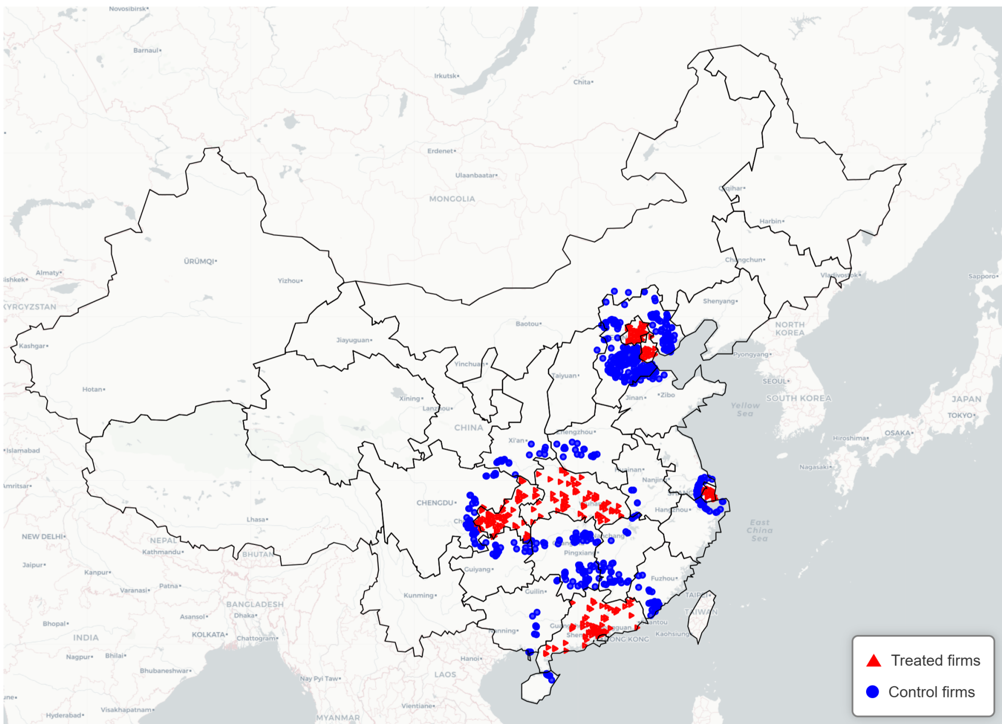

Figure 1: Geographical distribution of treated and matched firms

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

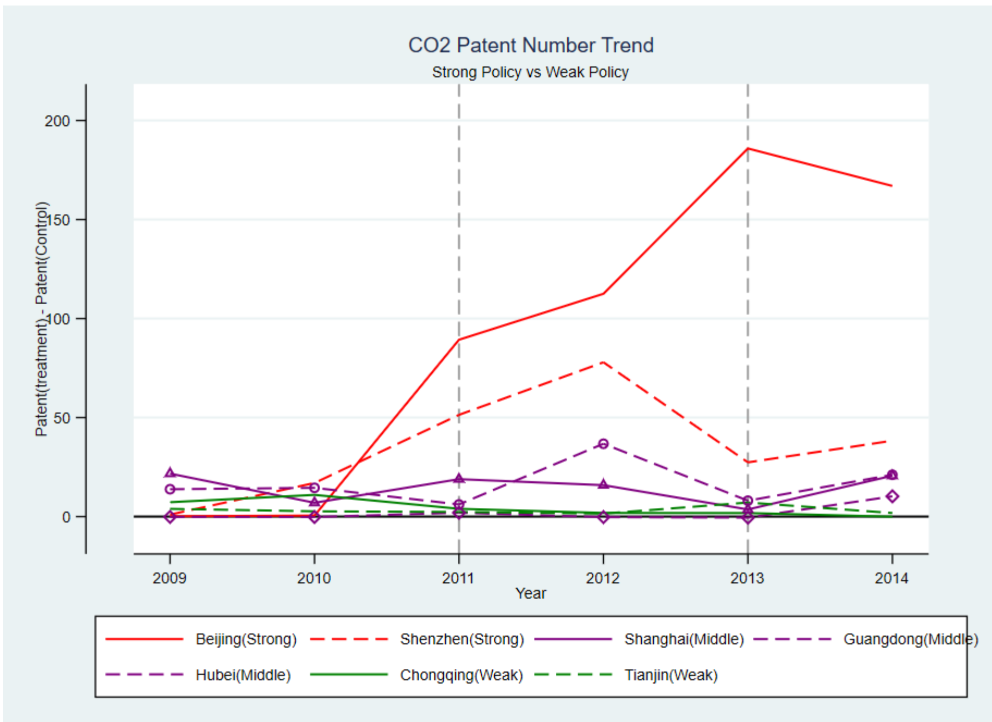

Figure 2: The average number of decarbonization-related patents

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

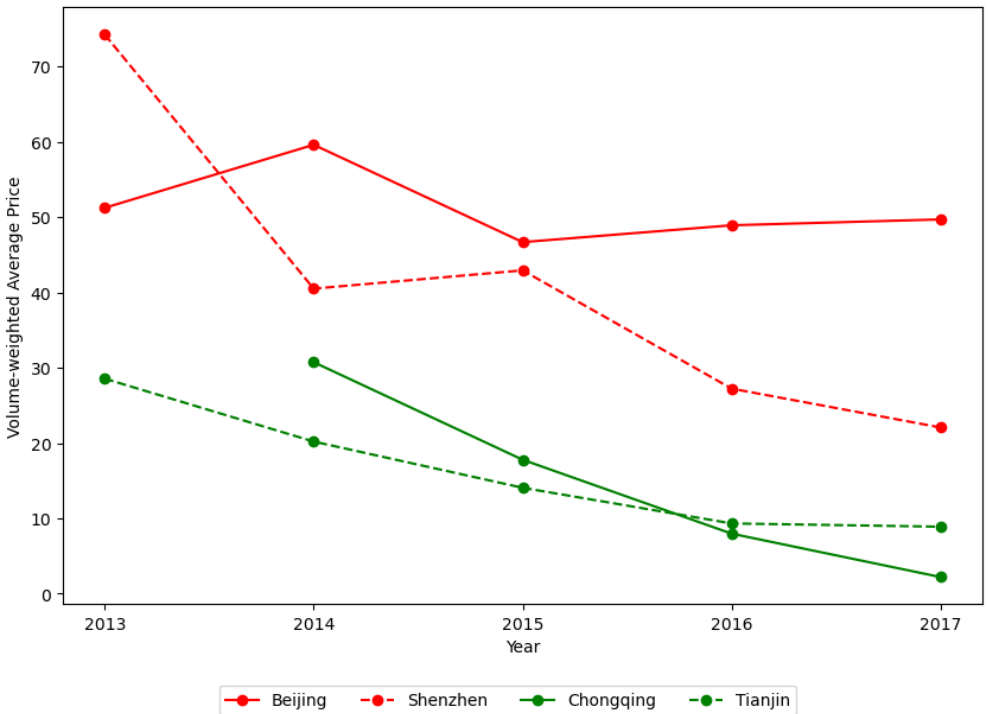

Figure 3: Average annual carbon prices

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.

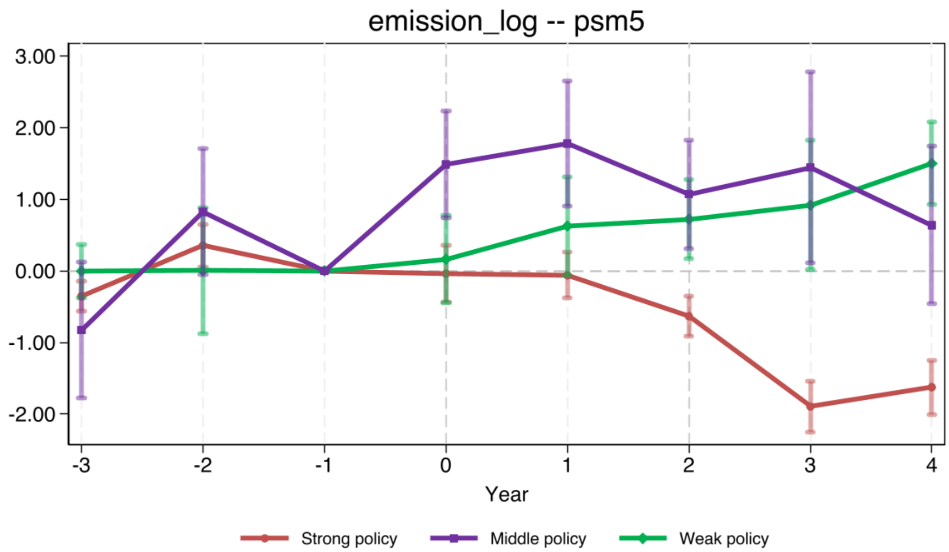

Figure 4: Parallel trend test for carbon emission

This figure presents the parallel trend test for 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.

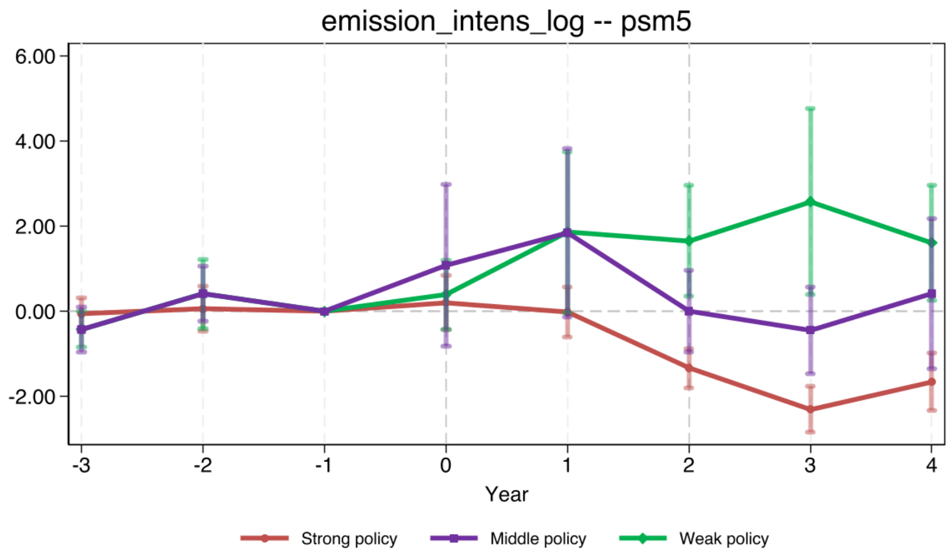

Figure 5: Parallel trend test for carbon emission intensity

This figure presents the parallel trend test for 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.

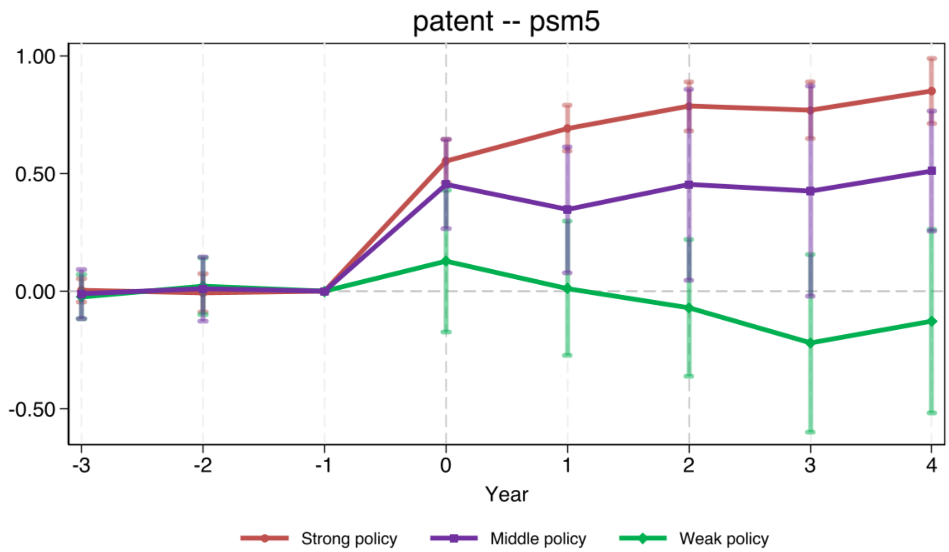

Figure 6: Parallel trend test for the number of carbon-related patents

This figure presents the parallel trend test for 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.

Table 1: Assessing environmental policy strictness, based on ex ante or ex post information

This table summarizes whether a region adopts strict environmental policies, based on the ex ante (Panel A) or ex post (Panel B) information. The ex ante information is collected before the announcements of pilot ETS, including 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)). The ex post information is disclosed carbon policies during implementing pilot ETS, including 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 environmental policies if it is strict in columns (1)–(3), weak environmental policies if it is weak in Columns (1)–(3), and middle otherwise.

	(1)	(2)	(3)	(4)
Panel A: Ex ante environmental policy strictness				
Region	Pollution fees	Government environmental budget	Green city rating	Policy strictness
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
Panel B: Ex post environmental policy strictness				
Region	Threshold	CT coefficient	TPS coefficient	Policy strictness
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 2:
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 5 firms from untreated neighborhood regions in the same industry, with similar carbon emissions and production in 2009 and 2010, 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	34,458	8.554	2.797	4,997	9.722	2.709
Carbon emission intensity	34,458	-1.985	4.017	4,997	-1.249	5.330
Production	36,430	11.409	2.042	6,746	12.406	1.868
Production equipment	43,270	9.969	2.473	9,212	11.490	2.146
Labor	45,007	5.352	1.726	9,530	6.501	1.562
Carbon patents	45,632	0.632	1.267	10,865	1.086	1.554

Table 3:
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 the pilot regional ETS on corporate outcomes, using the Callaway and Sant'Anna staggered difference-in-differences estimator (CSDiD) over the sample period through 2013, with the treatment cohort set to the 2011 regional-ETS announcement year. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. Wild cluster bootstrap standard errors of coefficient estimates, clustered at the firm level, are 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 absorbed by the CSDiD estimator. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Emission	Emission Intensity	Production	Carbon Patent
Strong Policy	-0.0893	-0.6374**	0.3001***	0.3932***
	(0.0824)	(0.2602)	(0.0855)	(0.0438)
Middle Policy	0.9849***	1.6143**	0.2150	0.1152
	(0.3410)	(0.8049)	(0.1797)	(0.1282)
Weak Policy	0.7918***	1.8984***	-0.3142	-0.0147
	(0.1700)	(0.5464)	(0.2661)	(0.1481)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	16260	16260	20654	27153

Table 4:
Corporate responses to the implementation of regional ETS: DiD for regions with strong, middle, and weak environmental policies, using matched sample

This table examines the implementation effect of the pilot regional ETS on corporate outcomes, using the Callaway and Sant'Anna staggered difference-in-differences estimator (CSDiD) over the sample period through 2016, with the treatment cohort set to each treated firm's actual regional-ETS launch year (2013 or 2014). Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. Wild cluster bootstrap standard errors of coefficient estimates, clustered at the firm level, are 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 absorbed by the CSDiD estimator. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Emission	Emission Intensity	Production	Carbon Patent
Strong Policy	-1.1556***	-1.5670***	0.1358**	0.0988***
	(0.1615)	(0.3009)	(0.0669)	(0.0312)
Middle Policy	-0.8507	-1.5285	0.3399	-0.0421
	(0.7974)	(1.0515)	(0.3134)	(0.1450)
Weak Policy	0.1331	1.6357	-0.5087*	0.1523
	(0.1300)	(1.1535)	(0.2824)	(0.1972)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	24723	24723	27218	35088

Table 5: Comparison of announcement and implementation effects by influential and non-influential firms

Panel A documents the announcement-period (2009–2013) difference-in-differences estimates for influential and non-influential firms, while Panel B documents the implementation-period (2011–2016) estimates. Dependent variables, expressed in logarithms, include carbon emission levels, carbon emission intensity, firm production, and carbon patent. Standard errors clustered at the industry level appear 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. *No-covariate fallback (Non-Influential Panel B only):* for each (sample, outcome) cell where the full specification omits at least one Strong/Middle/Weak region interaction as collinear with the absorbed fixed effects (a sign that a region×treatment sub-cell is too sparse once lagged-covariate-missing rows and singletons are dropped), the entire regression is re-run without the lagged controls so that all three region interactions are estimated under a uniform specification. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Emission		Emission Intensity		Production		Carbon Patent	
	Influential	Non-Influential	Influential	Non-Influential	Influential	Non-Influential	Influential	Non-Influential
Panel A: Announcement Effects (2009–2013)								
Strong	−0.2039*	−0.0180	−0.5472	−0.2783	0.5775***	0.0598	0.7985***	0.7008***
	(0.1095)	(0.0890)	(0.4386)	(0.2071)	(0.0914)	(0.0688)	(0.0576)	(0.0615)
Middle	1.3670***	2.2709*	1.8282***	0.1421	0.1579	2.0202**	0.3522***	0.2262
	(0.3057)	(1.3081)	(0.6668)	(0.6424)	(0.1709)	(0.8050)	(0.1291)	(0.3476)
Weak	0.6284**	0.1881	1.8075***	0.6771	−0.1662	−0.2673	0.0645	−0.1215
	(0.3136)	(0.1683)	(0.5176)	(0.4266)	(0.3016)	(0.4813)	(0.1275)	(0.3209)
Panel B: Implementation Effects (2011–2016)								
Strong	−2.0915***	−1.1759***	−2.0467***	−1.9969***	0.2325**	0.2251***	0.2843***	0.1842***
	(0.3270)	(0.1652)	(0.5832)	(0.2756)	(0.1032)	(0.0673)	(0.0484)	(0.0399)
Middle	−0.1521	−1.3360	−0.5194	−1.6425	−0.1514	−0.2536	−0.0182	0.0546
	(0.3050)	(1.9963)	(0.4623)	(1.9427)	(0.4896)	(0.3045)	(0.1149)	(0.5497)
Weak	0.1731	1.2850***	0.4365	1.7432	−0.4473**	0.0251	0.0583	0.2388
	(0.1887)	(0.4409)	(1.1138)	(1.1278)	(0.2166)	(0.1728)	(0.0881)	(0.3202)

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, and the number of carbon patents in Column (1)–(4), 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) Carbon Patent
Strong Placebo	-0.3540	0.6638	-0.1150	0.0650
	(0.3210)	(0.6553)	(0.3177)	(0.0767)
Middle Placebo	-0.1354	-0.1111	0.4771**	0.0850
	(0.2233)	(0.3807)	(0.1885)	(0.0659)
Weak Placebo	0.0970	-0.3723	-0.7319*	0.0927
	(0.4020)	(1.0523)	(0.4342)	(0.1958)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	12115	9985	11304	13778

Table 7:
Corporate responses to the announcements of regional ETS: DiD for firms with strong, middle, and weak IRM-based policy expectations, using matched subsidiary sample

This table examines the announcement effect of pilot regional ETS on corporate outcomes by firms' policy expectation, using difference in difference method over the period from 2007 to 2013, on the PSM-matched subsidiary panel. Treated firms are sorted into Strong, Middle, and Weak policy expectation tiers based on the first principal component of the five carbon-keyword tier-hit counts in their investor relations management (IRM) records during 2011–2013. The Strong tier comprises the 14 highest-scoring firms; firms whose IRM records contain no carbon-policy keyword are assigned to the Weak tier; the remaining firms with IRM records form the Middle tier. The unit of observation is the subsidiary tax-paying entity –year, with subsidiaries inheriting the policy expectation tier of their parent listed firm. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. Wild cluster bootstrap standard errors of coefficient estimates, clustered at the firm level, are 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 absorbed by the CSDiD estimator. City-by-year fixed effects are added. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Carbon Patent
Strong Expectation	-1.0879*	-2.0866***	0.5785**	0.7210**
	(0.6360)	(0.6768)	(0.2341)	(0.3128)
Middle Expectation	-0.4153	-5.1176	-0.2820	0.0584
	(0.4640)	(3.4240)	(0.1961)	(0.1897)
Weak Expectation	0.6889**	0.9552**	-0.2357	0.2307
	(0.3508)	(0.4288)	(0.1749)	(0.3277)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	1115	1115	1114	1318

Table 8:
Corporate responses to the implementation of regional ETS by allowance allocation design: TPS and CT

This table examines the implementation effect of the pilot ETS on corporate outcomes by allowance allocation designs, using the Callaway and Sant'Anna staggered difference-in-differences estimator over the sample period through 2016, with the treatment cohort set to each treated firm's actual ETS launch year (2013 or 2014). Panel A reports results for the Tradable Performance Standard (TPS) pilot regions together with their matched control firms. Panel B reports results for the Cap-and-Trade (CT) pilot regions together with their matched control firms. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. Wild cluster bootstrap standard errors of coefficient estimates, clustered at the firm level, are 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 absorbed by the CSDiD estimator. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
	Emission	Emission Intensity	Production	Carbon Patent
Panel A: Tradable Performance Standard (TPS)				
Strong Policy	-1.2396***	-1.6928***	-0.3599	0.4369*
	(0.1133)	(0.2565)	(0.3045)	(0.2304)
Middle Policy	-2.0389**	-2.2094***	-0.1302	0.2108
	(0.9070)	(0.8361)	(0.1446)	(0.2482)
Weak Policy	0.0751	0.0981	-0.1783	0.3443
	(0.1879)	(0.3886)	(0.1332)	(0.3003)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	2885	2885	3004	3740
Panel B: Cap-and-Trade (CT)				
Strong Policy	-1.1398***	-1.5636***	0.1572**	0.0862***
	(0.1671)	(0.2997)	(0.0688)	(0.0282)
Middle Policy	-0.8131	-1.5213	0.3583	-0.0227
	(0.7481)	(1.0426)	(0.3354)	(0.1403)
Weak Policy	0.1554	1.8772	-0.5736*	0.1437
	(0.1376)	(1.2250)	(0.3193)	(0.2246)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	22555	22555	25025	32401

Table 9: Corporate responses to the implementations of national ETS

This table examines the impacts of national ETS on firms in pilot regions (Beijing, Shanghai, Shenzhen, Guangdong, Hubei, Tianjin, and Chongqing), 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 10: 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. Allowance per firm, carbon patent, carbon emission, and carbon emission intensity are all in logarithm. 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 log(carbon patent+1)	-0.954***			-2.143***			-0.048***		
	(0.199)			(0.511)			(0.014)		
Lagged carbon emission		-0.005			0.324***			0.011***	
		(0.337)			(0.077)			(0.004)	
Lagged carbon emission intensity			0.159			0.232***			0.005
			(0.261)			(0.073)			(0.004)
Lagged GDP	1.021**	0.475	0.417	0.571	0.753***	0.781**	0.021**	0.007	0.017
	(0.427)	(0.612)	(0.613)	(0.377)	(0.271)	(0.305)	(0.010)	(0.011)	(0.012)
Lagged other pollution fees	-0.240	0.320	0.230	0.618**	-0.088	0.031	-0.029***	-0.028***	-0.023**
	(0.350)	(0.573)	(0.505)	(0.254)	(0.231)	(0.254)	(0.009)	(0.009)	(0.010)
N	23	23	23	16	21	21	25	27	27

Table 11: Governments' responses to corporate actions: A placebo test using non-pilot neighbour provinces

This table reports a placebo version of Table 10. The dependent variable is the pilot-province annual policy-stringency measure (Allowance per firm in Panel A; TPS coefficient in Panel B; CT coefficient in Panel C). The key independent variable replaces pilot-province firms' corporate actions with the mean of the same firm-level outcome computed across three non-pilot neighbour provinces of each pilot, lagged by one year. Each pilot has a unique three-neighbour set drawn from its direct geographical adjacency. Allowance per firm, carbon patent, carbon emission, and carbon emission intensity are all in logarithm. Control variables include the natural logarithm of local GDP and the natural logarithm of other pollution fees, both 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 log(carbon patent+1)	-39.299			74.310			-1.335		
	(72.240)			(48.467)			(1.377)		
Lagged log(carbon emission)		-0.168			-0.190			0.004	
		(0.332)			(0.258)			(0.008)	
Lagged carbon emission intensity			-0.462			-0.282			0.003
			(0.323)			(0.228)			(0.006)
Lagged GDP	0.323	0.415	0.708	1.084***	0.807*	0.910**	0.016	0.022*	0.020*
	(0.669)	(0.620)	(0.604)	(0.418)	(0.434)	(0.408)	(0.013)	(0.013)	(0.012)
Lagged other pollution fees	0.274	0.261	0.282	0.212	0.027	0.095	-0.020**	-0.017*	-0.018*
	(0.492)	(0.498)	(0.466)	(0.332)	(0.343)	(0.327)	(0.010)	(0.010)	(0.010)
N	23	23	23	21	21	21	27	27	27

Table 12: Governments' responses to corporate policy expectation

This table examines whether the firm-level IRM policy-expectation classification (Section 2.4) predicts pilot-province policy stringency. The dependent variable is the pilot-province annual policy-stringency measure (Allowance per firm in Column (1); TPS coefficient in Column (2); CT coefficient in Column (3)). The key independent variable, *N. strict-tier listed firms*, is the count of listed firms in each (province, year) whose IRM-PCA classification is in the top ("strict") tier, constructed from listed-firm IRM records during 2011–2013. Listed firms enter the province-year only after their listing year. The sample is restricted to year $\geq$ 2013 (post-implementation period). Allowance per firm in Column (1) is in logarithm. Control variables include the natural logarithm of local GDP and the natural logarithm of other pollution fees, both 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)
N. strict-tier listed firms	-1.173***	-0.662***	-0.021***
	(0.138)	(0.163)	(0.005)
Lagged GDP	1.961***	1.684***	0.046***
	(0.305)	(0.348)	(0.011)
Lagged other pollution fees	-0.674***	-0.637**	-0.034***
	(0.245)	(0.298)	(0.009)
N	26	26	33

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.

Table A.1: 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 A.2: 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 A.3: 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 A.4: 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 A.5: 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 A.6: 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 A.7: 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, non-ferrous 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, non-ferrous 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, non-ferrous 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, non-ferrous 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 A.8: Allocation Policy in Chongqing

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

B Pollution fees

Table B.9: 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.10: 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.11.

Table D.11: 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.

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.[8] 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.

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

E First-stage IV regression

Table E.12: 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

F IRM Keyword Dictionary

This appendix reports the Chinese keyword dictionary used to construct the IRM policy-expectation score in Section 2.4. The dictionary is built by starting from official ETS policy documents and expanding through co-occurring terms in the IRM transcripts of treated listed firms. The 97 terms are grouped by closeness to the pilot ETS into five groups, and the exclusion-list of 19 terms removes the usages of the word carbon which are irrelevant to carbon policy from the carbon-policy hit counts. Table F.13 reports the full dictionary with the rationale and sources for each group.

Table F.13: IRM keyword dictionary: 97 keywords across 5 weighted tiers and a 19-term black-list

This table reports the Chinese keyword dictionary used to construct the IRM policy-expectation score in Section 4.6. Five tiers (T1–T5) are ordered by how directly each term refers to the pilot ETS. The black-list contains material and chemistry uses of the character carbon that are replaced with a placeholder before tier counting so that they cannot pollute the carbon-policy hit counts. N is the number of terms in each tier. Source citations: National Development and Reform Commission (NDRC) document NDRC 2011-2601 is the Notice launching the carbon-trading pilot, October 2011; Guofa [2011] No. 41 is the State Council 12th Five-Year Plan for greenhouse-gas control; Guofa [2011] No. 26 is the State Council 12th Five-Year Plan for energy conservation and emission reduction; NDRC 2012-1668 is the China Certified Emission Reduction (CCER) interim rules; and the United Nations Framework Convention on Climate Change (UNFCCC) here refers to the Kyoto Protocol and the Conference of the Parties (COP) meetings COP-15 through COP-18 relevant to the 2011–2013 announcement window.

Tier	Weight	N	Rationale	Keywords
T1	10	15	Direct ETS policy and official names of China's carbon-trading pilot. Source: NDRC 2011-2601 launches the pilot; Guofa [2011] No. 41 defines the allowance mechanism.	carbon emissions trading market, carbon emissions trading pilot, carbon emissions trading, carbon emission trading, carbon emission right, carbon trading, carbon market, carbon allowance, carbon emission allowance, emission allowance, emission right trading, cap-and-trade, cap and trade, carbon finance, carbon emission total control.
T2	7	26	Carbon-related core concepts including emission language, measurement, offset mechanisms, and international framework. Source: emission concepts and MRV requirements from Guofa [2011] No. 41; CCER per NDRC 2012-1668; international framework from UNFCCC (Kyoto Protocol and COP-15 to COP-18).	carbon emission, carbon emit, CO_2 emission, carbon intensity, carbon footprint, carbon accounting, carbon inventory, carbon disclosure, carbon credit, CCER, certified emission reduction, Clean Development Mechanism, CDM, Kyoto Protocol, Copenhagen, Cancun, Durban, Doha, carbon tax, pollution-permit trading, low-carbon economy, low-carbon development, low-carbon transition, compliance, allowance allocation.
T3	5	22	Climate and energy framework. Source: greenhouse-gas and climate-change language from UNFCCC and the Intergovernmental Panel on Climate Change (IPCC) AR4/AR5 reports; energy-intensity indicators per Guofa [2011] No. 26.	greenhouse gas, climate change, global warming, energy saving and emission reduction, emission-reduction target, energy intensity per GDP, energy intensity, carbon neutrality, carbon peak, 3060, low-carbon, clean energy, renewable energy, new energy, energy consumption, wind power, photovoltaic, clean production, waste heat, energy-consumption reduction, renewable, low-energy-consumption.
T4	3	11	Broad environmental terms.	energy saving, environmental protection, green development, green economy, green finance, sustainable development, pollution reduction, desulfurization and denitrification, environmental protection, circular economy, desulfurization.
T5	1	4	Corporate sustainability and governance and the broadest signal. Lowest weight because these terms barely distinguish carbon-policy attention in 2011–2013 IR records, as ESG entered the Chinese listed-firm vocabulary later.	environmental governance, ESG, social responsibility, CSR.
Black	0	19	False-positive material and chemistry uses of the character carbon. Replaced with a placeholder before tier matching so that materials, chemistry compounds, industrial inputs, and the metric carbon content cannot trigger Tier-2 carbon-emission counts.	carbon fiber, carbon (material), carbon steel, low-carbon steel, super-low-carbon steel, medium-carbon steel, high-carbon steel, carbonate, lithium carbonate, calcium carbonate, carbon powder, carbon black, activated carbon, silicon carbide, carbonization, carbon content, content of carbon, activated carbon (alt), carbon (chemistry).

G IRM-covered vs. non-covered treated listed firms

Of the 182 treated listed firms in our sample, 53 have at least one IRM record during the 2011–2013 announcement window. If IRM coverage correlates with firm size or emission level, the firm-level expectation-group results in Section 4.6 could pick up selection rather than expectation. Table G.14 compares the IRM-covered and non-covered groups along the dimensions used in the main analysis (log assets, log production, log carbon emission, and log carbon emission intensity), with a two-sample *t*-test for the equality of means.

Table G.14: IRM-covered vs. non-covered treated listed firms: summary comparison

This table compares IRM-covered and non-covered treated listed firms during the window 2007–2013. Firm-level variables are first aggregated to the parent listed firm-year by summing levels across treated subsidiaries, then averaged across 2007–2013 within each parent, and finally logged. Columns (1) and (2) report group means; Column (3) reports the difference (IRM-covered minus non-covered); Column (4) is the two-sample t-statistic. ***, **, * indicate that the means differ at the 1%, 5%, and 10% level, respectively.

	(1) IRM-covered	(2) Non-covered	(3) Difference	(4) t-statistic
Log assets	13.4805	13.9835	-0.5030*	1.6683
Log production	12.9711	12.9427	0.0285	-0.0723
Log carbon emission	9.0691	10.0390	-0.9699	1.4968
Log carbon emission intensity	-3.7725	-2.9844	-0.7880	1.3417
Listed firms	41	107		

H Continuous IRM policy-expectation score and corporate carbon outcomes

This appendix complements the group-based DiD evidence in Section 4.6 by treating the IRM policy-expectation score as a continuous variable. We regress each year-t outcome on the firm-year IRM PC1 score over the 2011–2013 announcement window, estimated separately on the ETS-treated and non-treated subsidiary samples. Table H.15 reports the analytic cluster-robust specification, and Table H.16 reports the randomization-inference version.

Table H.15:
Continuous IRM policy-expectation score and corporate carbon outcomes

This table reports OLS regressions of corporate carbon outcomes on the firm-year IRM policy-expectation score, estimated over the 2011–2013 announcement window. Panel A reports results for the subsidiaries of the 27 ETS-treated listed firms with carbon-related investor-relations (IRM) Q&A text in 2011–2013. Panel B reports the placebo specification on subsidiaries of the 261 non-treated listed firms in the matched panel, with the same yearly joint-PCA construction of IRM PC1. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. IRM PC1 is the first principal component of the z-scored carbon-keyword hit counts (T1–T5) computed from each firm's IRM Q&A text in year t; PCA loadings are estimated each year jointly across treated and non-treated firms with at least one carbon-keyword hit, and firm-years with no carbon talk are assigned IRM PC1 $= 0$. Cluster-robust standard errors of coefficient estimates, clustered at the listed-firm (parent) level, are 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). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Carbon Patent
Panel A: ETS-treated firms				
IRM PC1	-5.037**	-5.174**	-0.179	-0.187
	(2.531)	(2.624)	(0.449)	(0.724)
Asset_{t-1}	-1.038**	-0.509	0.218	0.733**
	(0.421)	(1.311)	(0.380)	(0.358)
Liability_{t-1}	0.833**	-0.214	0.342	0.425**
	(0.407)	(1.225)	(0.292)	(0.212)
Other Controls	Y	Y	Y	Y
N	25	25	25	26
Panel B: Placebo, non-treated firms				
IRM PC1	-0.400	-0.269	-0.393*	0.862***
	(0.403)	(0.441)	(0.225)	(0.325)
Asset_{t-1}	-0.123	-0.734***	0.541***	0.588***
	(0.166)	(0.206)	(0.076)	(0.079)
Liability_{t-1}	0.802***	0.734***	0.231***	-0.145**
	(0.153)	(0.169)	(0.063)	(0.074)
Other Controls	Y	Y	Y	Y
N	632	632	617	680

Table H.16:
Randomization-inference version of Table H.15

This table reports the randomization-inference (RI) version of Table H.15. Panel A reports results for the subsidiaries of the 27 ETS-treated listed firms with carbon-related IRM Q&A text in 2011–2013. Panel B reports the placebo specification on subsidiaries of the 261 non-treated listed firms in the matched panel, with the same yearly joint-PCA construction of IRM PC1. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. IRM PC1 is the first principal component of the z-scored carbon-keyword hit counts (T1–T5) computed from each firm's IRM Q&A text in year t; PCA loadings are estimated each year jointly across treated and non-treated firms with at least one carbon-keyword hit, and firm-years with no carbon talk are assigned IRM PC1 = 0. P-values for the IRM PC1 coefficient are obtained from randomization inference (RI), block-permuting each listed parent's whole-history PC1 trajectory across listed parents in the sample. RI p-values are reported in square brackets below the IRM PC1 coefficient, and stars on that row reflect the RI p-values. Cluster-robust standard errors (clustered at the listed-firm level) are reported in parentheses below the Asset and Liability coefficients, with stars on those rows reflecting the analytic two-sided p-values. Control variables include the natural logarithm of total assets (lagged by one year) and the natural logarithm of total liabilities (lagged by one year). ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Carbon Patent
Panel A: ETS-treated firms				
IRM PC1	-5.037*	-5.174*	-0.179	-0.187
	[0.081]	[0.073]	[0.518]	[0.458]
Asset_{t-1}	-1.038**	-0.509	0.218	0.733**
	(0.421)	(1.311)	(0.380)	(0.358)
Liability_{t-1}	0.833**	-0.214	0.342	0.425**
	(0.407)	(1.225)	(0.292)	(0.212)
Other Controls	Y	Y	Y	Y
N	25	25	25	26
Panel B: Placebo, non-treated firms				
IRM PC1	-0.400	-0.269	-0.393	0.862*
	[0.532]	[0.778]	[0.258]	[0.092]
Asset_{t-1}	-0.123	-0.734***	0.541***	0.588***
	(0.166)	(0.206)	(0.076)	(0.079)
Liability_{t-1}	0.802***	0.734***	0.231***	-0.145**
	(0.153)	(0.169)	(0.063)	(0.074)
Other Controls	Y	Y	Y	Y
N	632	632	617	680

I Robustness check: Conventional DiD

Table I.17:
Corporate responses to the announcements of regional ETS: TWFE 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 conventional TWFE DiD method over the period from 2009 to 2013. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), 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)	(2)	(3)	(4)
	Emission	Emission Intensity	Production	Carbon Patent
Strong Policy	-0.0963	-0.3192	0.2759***	0.7670***
	(0.0741)	(0.1943)	(0.0659)	(0.0441)
Middle Policy	1.4761***	1.7272***	0.2666	0.3378***
	(0.3007)	(0.6202)	(0.1735)	(0.1221)
Weak Policy	0.6092**	1.6775***	-0.1733	0.0355
	(0.2671)	(0.4506)	(0.2396)	(0.1244)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	22054	22054	25369	31616

J 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:

$$
\begin{aligned}
y_{i,t} = {} & \beta_1 Treatment_i + \beta_2 Post_t + \beta_3 Strong_i \\
& + \beta_4(Treatment_i \times Post_t) + \beta_5(Treatment_i \times Strong_i) + \beta_6(Post_t \times Strong_i) \\
& + \beta_7(Treatment_i \times Post_t \times Strong_i) + \eta_i + \sigma_t + \epsilon_{i,t},
\end{aligned}
\tag{11}
$$

where $y_{i,t}$ is the outcome variable for firm i (carbon emission, carbon emission intensity, production, or carbon-related patents); $Treatment_i$ 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 for treated firms in strong-policy regions (Beijing or Shenzhen) and for their PSM matched control firms (a control firm is marked $Strong$ if it was matched to at least one Strong-region treated firm via the Mahalanobis distance procedure), and zero otherwise (treated firms in middle- or weak-policy regions and their matched controls); $Post_t$ 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. Because η_i and σ_t absorb all time-invariant firm characteristics and all common-year shocks, the firm-level constants $Treatment_i$, $Strong_i$, and $Treatment_i \times Strong_i$ are absorbed by η_i, and the year-level indicator $Post_t$ is absorbed by σ_t; only β_4, β_6, and β_7 are estimated, and β_7 on the triple interaction is the headline coefficient of interest. For the implementation results in Table J.19 we estimate a stacked variant of the design: stacks are constructed for each ETS-start cohort (2013 or 2014) with the never-treated matched controls appended to every stack, and $Post_t$ is redefined within each stack as the indicator that the calendar year is at or after that stack's cohort year, so that $Post_t$ varies by calendar year for every firm inside the stack. A stack-fixed effect is added to the absorption set.

Table J.18 reports the panel regression results for announcement effects. The significantly positive coefficients of the interaction term $Post \times Treatment$ in Columns (1) and (2) indicate that firms in regions with weak or middle environmental policies strategically increased the level and intensity of carbon emission after ETS announcements. The significantly negative coefficients on the triple interaction term $Treatment_i \times Post_t \times Strong_i$ in Columns (1) and (2) indicate that firms in regions with strong environmental policies decreased their carbon emission. Column (4) shows that these firms increase their investment in low-carbon technology. Table J.19 reports the implementation effects. It also shows significantly negative coefficients on the triple interaction term $Treatment_i \times Post_t \times Strong_i$ in Columns (1) and (2), suggesting firms in regions with strong environmental policies further decreased their carbon emission after implementation.

Table J.18:
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, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. *Strong* equals one for treated firms in strong-policy regions (Beijing or Shenzhen) and for their PSM matched control firms (a control firm is marked *Strong* if it was matched to at least one Strong-region treated firm via the Mahalanobis distance procedure), and zero otherwise (treated firms in middle- or weak-policy regions and their matched controls). 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. Consequently the single $Treatment$, $Post$, and $Strong$ main effects, as well as the firm-level $Treatment \times Strong$ interaction, are absorbed by the fixed effects and not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Carbon Patent
Post × Treatment	0.717***	1.329***	-0.002	0.186*
	(0.179)	(0.353)	(0.151)	(0.109)
Post × Treatment × Strong	-0.618***	-1.344***	0.285*	0.565***
	(0.194)	(0.401)	(0.165)	(0.121)
Post × Strong	-0.432***	-0.674***	-0.015	0.039
	(0.088)	(0.112)	(0.043)	(0.046)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	22054	22054	25369	31616

Table J.19:
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 a stacked DiDiD design over the period from 2011 to 2016. Corporate outcome variables are carbon emission, carbon emission intensity, firm production, and the number of carbon patents in Column (1)–(4), respectively. All dependent variables are in logarithm. *Strong* equals one for treated firms in strong-policy regions (Beijing or Shenzhen) and for their PSM matched control firms (a control firm is marked *Strong* if it was matched to at least one Strong-region treated firm via the Mahalanobis distance procedure), and zero otherwise. Stacks are constructed for each ETS-start cohort (2013 or 2014), with the never-treated matched controls appended to every stack; within each stack, *Post* is defined as the indicator that the calendar year is at or after that stack's cohort year, so that *Post* varies by calendar year for every firm inside the stack. 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) plus a stack-fixed effect are included. Consequently the single $Treatment$, *Post*, and *Strong* main effects, as well as the firm-level $Treatment \times Strong$ interaction, are absorbed by the fixed effects and not reported. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Emission	(2) Emission Intensity	(3) Production	(4) Carbon Patent
Post × Treatment	-0.114	-0.348	-0.210	0.116*
	(0.156)	(0.727)	(0.178)	(0.070)
Post × Treatment × Strong	-1.263***	-1.431*	0.319*	0.035
	(0.225)	(0.781)	(0.184)	(0.072)
Post × Strong	0.047	-0.019	0.009	0.017
	(0.036)	(0.057)	(0.022)	(0.017)
Fixed Effects	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
N	41609	41609	39167	45316