Carbon Leakage within Firm Ownership Networks*

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Abstract

This paper evaluates the carbon leakage of China's regional pilots of emission trading system (ETS). Our analysis leverages firm-level tax records, ownership networks, and the quasi-experimental nature of the ETS pilots. We find that ETS-regulated firms shift production to their unregulated sister entities in the same ownership network, resulting in an 8.3% increase in carbon emissions from these unregulated partners. We also show that the leakage mainly occurs among low-emission firms, under the mass-based allocation rule, and in areas with low regulatory risks. Accounting for carbon leakage, the aggregate effect of China's ETS pilots on firm emissions becomes statistically insignificant.

Keywords: Carbon Leakage; Emission Trading System; Climate Change
JEL Codes: Q58, H23, O40

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1 Introduction

Climate change presents a global challenge that requires coordinated efforts to reduce greenhouse gas (GHG) emissions across all regions. However, the existence of leaders and laggards in climate action among different jurisdictions has resulted in varying levels of regulatory stringency. The fragmentation and localization of climate policies, which often focus on specific regions or industries (such as California's cap-and-trade program and China's regional ETS pilots), have led to divergent shadow prices for carbon emissions. The effectiveness of such uncoordinated and unilateral carbon pricing regimes is debatable. On the one hand, explicit carbon prices have shown the potential to incentivize emission reductions while minimizing economic impacts.[1] On the other hand, the incomplete coverage of policies may give rise to carbon leakage, where emissions reduced in one jurisdiction are offset by increased emissions in another. This phenomenon jeopardizes global climate integrity and undermines the cost-effectiveness of climate mitigation efforts (Böhringer et al., 2022; Fowlie and Reguant, 2022).

Understanding carbon leakage is critical to evaluate the effectiveness of location-specific climate policies. However, the identification of carbon leakage poses several empirical challenges (Fowlie and Reguant, 2018). Rarely do exogenous variations in GHG regulation stringency occur across regions, making it difficult to isolate the causal effects. Many existing studies attempt to capture leakage risks by leveraging asymmetries in energy prices and industry-level energy intensities (Cosbey et al., 2019). These proxies for regulation leakage are likely to be correlated with other factors that influence emissions, thereby becoming endogenous. Therefore, constructing appropriate counterfactuals to identify shifts in carbon emissions and isolate the specific leakage locations presents a significant challenge. Moreover, there is a scarcity of direct measures for carbon leakage. The current literature often relies on proxies such as carbon-embodied trade flows, which may fail to trace emission spillovers accurately.

[1] A large body of literature has assessed the effect of carbon pricing in reducing emissions, such as California's cap-and-trade program (Hernandez-Cortes and Meng, 2023), the EU ETS (Martin et al., 2014; Jaraite and Di Maria, 2016; Borenstein et al., 2019; Bayer and Aklin, 2020; Colmer et al., 2022; Dechezleprêtre, Nachtigall and Venmans, 2023), and China's regional ETS pilots (Cao et al., 2021; Cui et al., 2021). A growing literature has also explored the impact of carbon pricing on various economic outcomes, including firm profits (Linn, 2010), competitiveness (Joltreau and Sommerfeld, 2019), stock values (Veith, Werner and Zimmermann, 2009; Bushnell, Chong and Mansur, 2013), low-carbon innovation and adoption (Taylor, 2012; Borghesi, Cainelli and Mazzanti, 2015; Calel and Dechezleprêtre, 2016; Cui, Zhang and Zheng, 2018; Calel, 2020; Cui, Zhang and Zheng, 2021), management practices (Yong et al., 2021), and other economic adjustments (Commins et al., 2011; Martin, Muûls and Wagner, 2016; Marin, Marino and Pellegrin, 2018).

This paper aims to investigate the occurrence of carbon leakage at the firm level within the context of China's regional carbon market pilots. The ETS pilots, varying across regions, sectors, and years, provide plausibly exogenous variations in carbon pricing to identify carbon leakage and firms' responses. We utilize firms' ownership networks to construct the treatment and control groups. One would expect a parent company could shift emissions from ETS-regulated subsidiaries to unregulated ones, benefiting from existing knowledge sharing or established relationships that reduce the cost of reallocation (Giroud and Mueller, 2019; Chen et al., 2021*b*). Therefore, our treatment group consists of firms within the same ownership network as the ETS-regulated firms (referred to as ETS-sister firms). Our control group includes firms in an ownership network without any ETS-regulated firms. We employ a matching procedure to identify the most comparable unaffected firms to establish a suitable control group. By constructing a matched sample, we can estimate carbon leakage using a difference-in-differences (DID) approach, comparing the outcomes of ETS-sister firms to those of unaffected firms before and after the ETS launching. The empirical analysis utilizes firm tax records collected by the Chinese State Administration of Tax from 2008 to 2015. This dataset extensively covers firms across various sectors, offering comprehensive information on their geographical locations, economic characteristics, and production activities. Of particular importance is its inclusion of detailed energy consumption data, disaggregated by fuel sources such as coal, oil, natural gas, and electricity. With this rich dataset, we can measure emission emissions directly and gain insights into the dynamics of carbon leakage.

We present compelling evidence of carbon leakage within firm ownership networks. ETS-sister firms exhibit a substantial increase in carbon emissions following the announcement of ETS pilots, compared to similar firms without regulated firms in the ownership networks. The leakage effect is observed in both the announcement and trading phases, with a more pronounced impact during the latter. Our results withstand a series of robustness checks to account for confounding factors or alternative matching methods. The economic implications of our results are noteworthy. Cui et al. (2021) documents a 16.7% reduction in carbon emissions among ETS-regulated firms. In comparison, we show an 8.3% increase in carbon emissions among ETS-sister firms, indicating that a large portion of emissions were shifted to unregulated firms. A simple calculation indicates a carbon leakage rate of 45% (i.e., units of emissions leaked per unit of emissions abated).[2] The

[2]The mean carbon emission reported in Cui et al. (2021) is $63,576 = \exp(11.06)$ metric tons. In comparison, the

estimate aligns closely with the finding of Fowlie and Reguant (2022).[3]

To understand the underlying mechanisms, we investigate the impacts of carbon leakage on firm economic activities and energy consumption. ETS-sister firms exhibit significant increases in energy consumption, outputs, sales, and labor inputs. However, we find muted effects on their emission intensity, energy mix, energy efficiency, or productivity. These results suggest that the leakage occurs due to the shift of production activities from ETS-regulated firms to their unregulated sister entities instead of efficiency improvement. Furthermore, we uncover substantial heterogeneity along various dimensions of market designs and firm characteristics. The leakage effect is more pronounced among ETS-regulated firms exposed to higher carbon prices, greater turnover rates of carbon allowances, or mass-based allowance allocation. Regulated firms primarily reallocate production and emissions towards small and low-emission sister entities without ETS regulations. Additionally, we observe that emission leakage is predominantly concentrated in regions with lower regulatory risks, such as non-ETS regions with lower levels of air pollution. Finally, accounting for carbon leakage, China's ETS pilots increased emissions during the announcement phase, and the impacts became insignificant during the trading phase.

This paper provides the first empirical evidence of carbon leakage within firm ownership networks. The existing literature primarily relies on computational general equilibrium models to simulate the magnitude of carbon leakage (Carbone, 2013; Fischer and Fox, 2012; Baylis, Fullerton and Karney, 2014; Böhringer, Rosendahl and Storrøsten, 2017; Carbone and Rivers, 2017; Fowlie and Reguant, 2018, 2022). Some empirical works explore carbon leakage through international trade channels (Aichele and Felbermayr, 2015; Aldy and Pizer, 2015; Naegele and Zaklan, 2019). Recent research has examined carbon leakage among multinational firms under the EU ETS (Dechezleprêtre et al., 2022). In contrast, we employ regional variations in carbon regulation and a quasi-experimental design to provide causal evidence of firm-level carbon leakage in a single country. By demonstrating that incomplete regulation and the network dynamics of corporate groups can significantly weaken the effectiveness of carbon pricing, our paper highlights the importance of regulating conglomerates that can reallocate emissions among their subsidiaries.

mean carbon emission in this study is $19,148 = \exp(9.86)$ metric tons. On average, one ETS-regulated firm has three unregulated sisters in our sample. With the abated rate of 16.7% and leaked rate of 8.3%, the rate of carbon leakage is $44.9\% = 3 \times (19,148 \times 8.3\%)/(63,576 \times 16.7\%)$.

[3] Fowlie and Reguant (2022) report that a median estimate of the leakage rate is 46% in the US.

Our work contributes to the debate on the effectiveness of place-based regulations or policy experimentation (Karplus, Zhang and Almond, 2018; Wang, Wu and Zhang, 2018; Martin, Nataraj and Harrison, 2017; Curtis, 2020; He, Wang and Zhang, 2020; Najjar and Cherniwchan, 2021). Many environmental policies specifically target particular geographic areas, such as the designation of non-attainment counties under the US Clean Air Act (Greenstone, 2002) or the establishment of Two Control Zones in China to limit SO_2 emissions (Cai et al., 2016). Moreover, the policy experimentation conducted by various governments often exhibits notable biases in site selections (Wang and Yang, 2021). The localized nature of these designs or the incomplete regulatory coverage can introduce biases in the estimated policy effects if the potential spillover from regulated regions to unregulated ones is overlooked. By capturing the policy-induced carbon leakage, this paper advances our understanding of the unintended consequences of place-based regulations.

Our results also extend the existing literature that empirically examines the spillover effects of local economic shocks (Giroud and Mueller, 2015; Seetharam, 2018; Giroud and Mueller, 2019)[4] and environmental regulations (Hanna, 2010; Gibson, 2019; Samy Soliman, 2019; Cui and Moschini, 2020; Chen et al., 2021*b*; Dechezleprêtre et al., 2022)[5]. By leveraging comprehensive ownership networks, detailed firm characteristics, and a wide range of policy variations, our study reveals a distinct channel within corporate conglomerates through which firms can propagate economic shocks or share regulatory pressures with other entities in the same ownership network. Importantly, our analyses shed light on the underlying mechanisms of carbon leakage by capturing detailed firm strategic behaviors in response to external shocks and examining how firms strategically reallocate their resources.

The remainder of this paper is organized as follows. Section 2 provides an overview of the empirical background and the conceptual framework. Section 3 outlines our research design and presents the econometric model. Section 4 details the data and variables. Section 5 presents the empirical results. Finally, Section 6 concludes.

[4]For instance, Giroud and Mueller (2015) and Giroud and Mueller (2019) study the effects of local economic shocks on resource reallocation and employment outcomes, and Seetharam (2018) analyze the spillover effects of a hurricane on disrupted and undisrupted plants within multi-plant firms.

[5]For instance, Hanna (2010) investigate the foreign direct investment decisions of multinational companies in response to county-level non-attainment status designated by the U.S. Clean Air Act, while Cui and Moschini (2020) examine the exit behavior of multi-plant firms. Gibson (2019) examine the cross-media pollution substitution within firms under the U.S. Clean Air Act. In contrast, Samy Soliman (2019) provides evidence of plant relocation and emission leakage. Chen et al. (2021*b*,*a*) investigate an energy-saving program in China and identify leakage from regulated subsidiaries to unregulated entities within the same conglomerate.

2 Background and Conceptual Framework

2.1 China's ETS Pilots

China has implemented regional carbon market pilots as part of its efforts to address the growing carbon emissions. In 2011, the National Development and Reform Committee (NDRC) approved the establishment of seven regional carbon market pilots. These pilots encompassed four municipalities: Beijing, Shanghai, Tianjin, and Chongqing; two provinces, Guangdong and Hubei; and one special economic zone, Shenzhen. Trading of carbon allowances began in 2013 following the launch of these pilots. While the NDRC provides general guidelines and oversees the planning and development of the ETS pilots, each pilot can design its own market rules, including sector coverage and allowance allocation, based on the provided guidelines (Zhang, Wang and Du, 2017). A summary of the ETS policy designs across the different pilots is presented in Table A1 in the Online Appendix.

China's ETS pilots exhibit three notable features. First, these carbon markets are localized, resulting in incomplete coverage. Only firms within the seven pilot regions are subject to ETS regulation and can participate in carbon trading. The sectoral coverage varies across pilots, spanning from manufacturing to non-manufacturing industries. Additionally, the pilots set different thresholds for firm coverage within each regulated sector, typically based on annual emissions or energy consumption. Such substantial variations across regions, sectors, and firms constitute the primary source of carbon leakage under China's ETS pilots.

Second, the pilot regions demonstrate significant heterogeneity in market designs, encompassing total emission allowances, allocation rules, and measurement, reporting, and verification (MRV) systems.[6] Furthermore, two main allocation rules are employed by the pilots: mass-based and rate-based. The former sets a cap on total emissions, while the latter regulates emission intensity (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2022).[7]

[6]The allocation of carbon allowances differs across pilots. For example, Guangdong issues the most carbon allowances (388 Metric tons [Mt]), while Shenzhen has the least (30 Mt). The share of emissions covered by each pilot ranges from 33 percent in Hubei to 60 percent in Tianjin. While most pilots allocate allowances for free, Guangdong and Shenzhen auction up to 3 percent of allowances. Carbon allowances can only be traded within each pilot, and noncompliance often incurs various financial and non-financial penalties.

[7]In the mass-based rule, regulators establish a predetermined total number of allowances for each compliance period. If a regulated entity's emission level exceeds allocated allowances, it must purchase additional allowances from the carbon market to comply. In most cases, the allocation of allowances remains unaffected by a facility's production level during the compliance period. Under the rate-based system, regulators set an emission intensity target for regulated

Third, the ETS pilots include the announcement phase (2011 to 2012) and the trading phase (since 2013). During the announcement phase, while the market design remains uncertain, firms in pilot regions may anticipate regulatory risks based on their historical emission levels and adjust to mitigate future compliance pressures. In the trading phase, detailed implementation rules lead to explicit carbon prices, imposing additional production costs on regulated firms. Consequently, the magnitude of carbon leakage may differ between these two phases.

2.2 Conceptual Framework of Carbon Leakage

The presence of a fragmented carbon market and localized policy design results in significant variations in the stringency of carbon regulation across regions and firms. Consequently, firms operating within a carbon ETS have incentives to reallocate their production activities, along with the associated carbon emissions, to non-pilot regions or unregulated entities, leading to carbon leakage. This phenomenon aligns with the pollution haven hypothesis (Levinson and Taylor, 2008).

Our paper focuses on one type of carbon leakage: firms reallocating production activities within the ownership networks. Figure 1 illustrates the conceptual framework. The black arrows represent the connections between one firm and several others through subsidiaries, investments, or shareholding. These firms collectively form an ownership network comprising entities affiliated with the same conglomerate.[8] Firms within an ownership network may benefit from lower costs of reallocation due to knowledge sharing or established relationships (Giroud and Mueller, 2015, 2019; Chen et al., 2021*a*,*b*). Consequently, this ownership network represents a boundary where carbon leakage is more likely to occur. Within this network, an ETS-regulated firm strategically manages compliance pressure by shifting production activities, and thus emissions, to its unregulated sister firms. In contrast, the firms that are not subject to ETS regulation and do not have any regulated sister firms within the ownership networks are unlikely to be affected.

[Insert Figure 1 about here]

firms. The number of allowances depends on a firm's output and historical emission rate, which may be adjusted at the end of each compliance period to account for changes in a firm's production level.

[8] A conglomerate refers to a group of parent and subsidiary corporations functioning as a single economic entity under a common source of control.

3 Empirical Strategy

3.1 Research Design and Econometric Model

We leverage firms' ownership networks to identify carbon leakage under China's ETS pilots. Figure 1 illustrates the definition of the treatment and control groups. The treatment group comprises unregulated firms with regulated sister entities (ETS-sister firms); the control group consists of unregulated firms without any regulated firms in the ownership networks. We estimate the causal effect of carbon pricing on leakage by comparing the emission outcomes of the treatment group to the control group before and after the implementation of the ETS.

We employ a matching approach to select the most comparable firms for ETS-sister firms to form the control group. Specifically, the matched firm in the control group is in the same sector and possesses the most similar firm-level attributes. We measure the similarity between the two firms using the Mahalanobis distance, calculated based on total emissions and emission intensity over the three years before the announcement of ETS pilots (i.e., 2008, 2009, and 2010).[9] This within-sector-year matching strategy effectively controls for sector-specific time-variant unobservables that may influence treated and control firms. We will conduct robustness checks using alternative matching estimators and different sets of matching covariates.

We conduct balancing tests to evaluate the credibility of our matching procedure. Figure 2 presents the mean differences in selected firm-level attributes between the two groups of firms, both for the unmatched sample (shown in the left panel) and the matched sample (shown in the right panel). In the unmatched sample, we observe significant disparities in emissions and key economic characteristics between the treatment and control groups for all three years preceding the ETS announcement (i.e., 2008, 2009, and 2010). However, these differences substantially diminish when we examine the matched sample. This indicates that our matching strategy has successfully identified and selected comparable control firms.

[9]The distance-based matching technique effectively identifies control units that closely resemble the treated ones by searching for control units with the closest values of characteristics. However, it is important to note that the performance of this approach may be compromised when there are too many covariates, typically exceeding eight (Rubin, 1979; Zhao, 2004; Stuart, 2010). In our study, selecting more covariates often reduces the number of matched pairs due to missing or dropped values in certain key economic indicators. We carefully choose covariates that exhibit strong correlations with the outcomes to address this issue. This selection ensures a close similarity between the treated and control units and a sufficient number of matched pairs for analysis. Moreover, we conduct the matching with replacement, which helps prevent the introduction of additional bias in the selection of control units. This approach ensures that each treated firm is matched with the closest possible control firm.

[Insert Figure 2 about here]

Using the matched sample, we employ a DID approach to estimate carbon leakage induced by China's ETS pilots. For firm i in sector j from province r in year t, we estimate the following regression model:

$$Y_{ijrt} = \beta_1 \text{Sister}_i \times \text{Announcement}_{it} + \beta_2 \text{Sister}_i \times \text{Trading}_{it} + \gamma_i + \delta_{jt} + \eta_{rt} + \varepsilon_{ijrt}. \quad (1)$$

The outcome variable, Y_{ijrt}, denotes carbon emissions (total emissions and emission intensity, in logarithms) or economic outcomes (output, input, and productivity). The dummy variable, Sister_i, is an indicator for ETS-sister firms, equalling one if firm i is unregulated but in an ownership network exposed to the ETS, and zero otherwise.[10] We include time indicators, Announcement_{it} and Trading_{it}, to capture the potentially different leakage effects during the announcement or trading phases. The parameters of central interest, β_1 and β_2, capture the leakage effects of China's ETS pilots in the announcement and the trading phases, respectively.

To account for unobservable determinants for carbon emissions, we include firm fixed effects γ_i to control for time-invariant firm attributes. We also add industry-year fixed effects δ_{jt} and province-year fixed effects η_{rt} to capture industry-specific and region-specific time-varying factors. Lastly, ε_{ijrt} is an idiosyncratic error term. We cluster the standard errors at the industry level to allow for within-industry correlations.

3.2 Identification Challenges

Parallel Trends Assumption. To ensure the validity of our DID design, it is crucial to examine whether the parallel trends assumption holds. This assumption states that in the absence of ETS pilots, the trends in firm outcomes would have followed a similar pattern between the treated and control groups. To support this assumption, we estimate an event-study model that analyzes the trends before the announcement of ETS pilots. This allows us to assess whether there are any systematic divergences in firm outcomes between the two groups over time.

[10]Specifically, as listed in Table A1, the announcement period refers to 2011-2012 while the trading period refers to 2013-2015 for ETS firms located in Beijing, Shanghai, Tianjin, and Guangdong. For other ETS firms in Chongqing and Hubei, the announcement period refers to 2011-2013, and the trading period refers to 2014-2015.

Confounding Policies. It is important to consider the presence of confounding policies that could potentially influence firms' emissions or production activities and confound our identification strategy. We acknowledge two notable policies that coexist with the ETS pilots.

First, in 2011, the Ministry of Ecology and Environment implemented stringent regulations targeting the Beijing-Tianjin-Hebei (BTH) area, one of China's most polluted regions. These regulations aimed to reduce local air pollution, especially $PM_{2.5}$. As carbon dioxide is often co-emitted with local air pollutants, such as coal burning, it is likely that these regional air pollution control measures also affect firms' carbon emissions. To address this concern, we conduct a robustness check by excluding firms in the BTH region from our analysis.

Second, the Top 10,000 Energy Saving (ES10K) program, initiated by the National Development and Reform Commission (NDRC) in late 2011, aimed to reduce energy consumption in Chinese industrial firms. This program covers the top 10,000 energy users in the manufacturing sector, accounting for about 60% of nationwide energy consumption in China (Filippini et al., 2020). The ES10K program can affect emissions of both directly regulated firms and unregulated but related firms (Chen et al., 2021*a*). To address this problem, we rerun the regression by including an indicator for the ES10K program or excluding firms potentially affected by this policy.

We also consider the presence of other overlapping industrial or regional policies, such as the "Action Plan on Air Pollution Prevention and Control" (known as "Air Ten"), which was announced in 2013 (Karplus, Zhang and Zhao, 2021). These policies can be captured by including flexible fixed effects at the industry-year and province-year levels in our analysis, thus accounting for their potential impact on firm emissions. By carefully addressing the potential influence of these confounding policies, we aim to strengthen the robustness of our findings and ensure the validity of our identification strategy.

Bias in Staggered DID. Recent literature points out the potential bias of the two-way fixed effects estimator with staggered treatment timing (De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). Under a setting with varied treatment timing and heterogeneous treatment effect, the bias arises from comparing later treated units and earlier treated units that instead serve as "controls." Our setting differs from other staggered DID studies in that we consider the treatment starts from the announcement of ETS pilots, which happens at the same time for all pilot regions. The time varies regarding when each pilot started trading as listed in Table A1. As a result, the announcement and trading effects are identified by comparing the treatment and control groups between the corresponding ETS phase (either announcement or trading) and the pre-announcement period. To further mitigate the concerns, we follow the intuition in Goodman-Bacon (2021) and check the robustness of our results by estimating the baseline model and the event study model separately for firms in different timing groups, i.e., those whose regulated sister firms started trading in 2013 and 2014, respectively.

4 Data

4.1 Data Sources

The primary data source for our study is the Chinese National Tax Survey Database (CNTSD), which is an extensive annual survey conducted jointly by the Ministry of Finance and the State Administration of Taxation of China. This database covers a wide range of industries and regions nationwide, providing detailed information on firms' geographic locations, sectors, and economic activities. It includes both large and small firms, including young firms, offering a comprehensive view of the manufacturing sector in China (Liu and Mao, 2019).

A notable feature of the CNTSD is its rich information on firm-level energy consumption, broken down by energy types such as coal, oil, natural gas, and electricity. This allows us to calculate firm-level carbon emissions using emission factors provided by China's Department of Energy Statistics. Unlike previous studies that rely on trade flows as a proxy for carbon leakage, our direct measurement of carbon emissions enables a more accurate assessment. Furthermore, we extract detailed firm-level production and balance-sheet information, including output, sales, investment, value-added, labor, capital, and material input purchases, among other variables.

To analyze the ownership networks of firms, we utilize data from China's Administrative Registration Database (CARD), maintained by the State Administration of Industry and Commerce. This database contains registration information for all firms in China, including their shareholders and subsidiaries. This dataset allows us to construct firms' ownership networks and identify ETS-sister firms.

Information on the specific ETS rules in the seven regional pilots is compiled from the official websites of local Development and Reform Commissions responsible for regulating carbon emissions and carbon markets. We summarize these rules in Table A1. We compile a list of regulated firms and classify them into rate-based or mass-based systems based on the reported allowance allocation rules in Table A2. Furthermore, we obtain carbon allowance trading data from the seven carbon exchanges, including price and volume.

4.2 Variable Construction

The main dependent variables in our study are carbon emissions and emission intensity. We consider both direct emissions from the combustion of fossil fuels and indirect emissions from electricity consumption. We utilize the energy consumption records from the CNTSD to calculate emissions, considering fuel-specific emission factors.[11] We also include measures of energy consumption in metric tons of standard coal equivalents, where 1 ton of coal equivalent equals 29,307 gigajoules (GJ). Furthermore, we measure emission intensity as total carbon emissions per value of gross outputs and energy intensity as energy consumption per value of gross outputs.

In addition to emissions-related variables, we incorporate various firm economic attributes, including outputs, value-added, sales, labor, capital, and material input purchases. Using these comprehensive firm characteristics, we calculate additional measures such as capital intensity (capital-labor ratio), labor efficiency (output-labor ratio), and capital efficiency (output-capital ratio). Firm-level productivity is assessed by measuring total factor productivity (TFP), following the standard approach in the economics literature (Olley and Pakes, 1996).

To capture the market performance of the seven ETS pilots, we utilize two indicators: average carbon price and turnover rates throughout the sample period. The average carbon price is a proxy for carbon regulation stringency. The turnover rate, which represents the ratio of trading volume to the total allowances issued, reflects market participation and activity in trading allowances. For non-ETS regions, carbon price and turnover rates are coded as zeros. These indicators provide insights into the functioning and dynamics of the carbon market in each pilot region.

[11] For detailed emission factors for each energy type, please refer to Appendix, Table A3.

4.3 Summary Statistics

We adopt a meticulous and rigorous data cleaning and merging process as in Cui et al. (2021).[12] This process includes the removal of observations with missing data, zero values, or drastic changes in key variables across years. Finally, the cleaned dataset includes 413 regulated firms and 40,219 unregulated firms. In total, there are 5,552 observations from 826 firms during the 2008 - 2015 period. Table 1 shows the summary statistics of firm carbon emission and energy consumption, firm economic attributes, and regional carbon market performance. All variables except for turnover rates are in logarithms.

[Insert Table 1 about here]

5 Results

In this section, we begin with the baseline results on the spillover effects of ETS on firm emissions. We then explore how the ETS leads to the reallocation of production activities. Moreover, we examine the heterogeneous effects along the following dimensions: firm characteristics, policy features, carbon market performance, and city air pollution levels. Lastly, we seek to provide some insights into the aggregate effect of the ETS on firm emissions.

5.1 Carbon Leakage Effects

We estimate the baseline model in Equation (1) using different combinations of fixed effects to capture unobservable firm-specific characteristics and time trends. Table 2 presents the coefficient estimates and standard errors. We decompose the leakage effects into the announcement and trading phases. The preferred model specification, reported in Column (3), includes the firm, province-year, and industry-year fixed effects.

[Insert Table 2 about here]

Our findings consistently show positive coefficients for total emissions in both the announcement and trading phases, indicating a statistically significant increase in total emissions from

[12]In the SI Appendix, Cui et al. (2021) document a detailed data cleaning process.

ETS-sister firms, which are unregulated firms within the same conglomerate as ETS firms. The preferred model estimate suggests that ETS-sister firms experienced a 6.7% increase in total emissions during the announcement phase, providing evidence that ETS firms began shifting their emissions after the announcement of ETS pilots. The effect becomes even larger during the trading phase when explicit carbon prices are introduced. On average, we observe an 8.3% increase in total emissions from ETS-sister firms after the start of trading. This increase is economically significant. To put it in context, a study by Cui et al. (2021) reports a 16.7% decrease in total emissions from ETS-regulated firms. Taken together, these results suggest that the regulated firms reallocate a substantial portion of their emissions to their unregulated sister firms.

The DID approach requires parallel trends in firm carbon emissions between the treatment and control groups in the absence of the ETS pilots. To provide evidence, we estimate the dynamic effect using an event study model, considering the announcement of ETS pilots as the start of treatment. Specifically, we include leads and lags of the ETS-announcement dummy in the baseline regression to trace out the year-by-year effects:

$$Y_{ijrt} = \sum_{\substack{-3 \leq k \leq 4 \\ k \neq -1}} \beta_k \text{Sister}_i \times \text{ETS}_{t-k} + \alpha_i + \delta_{jt} + \lambda_{rt} + \varepsilon_{ijrt}. \quad (2)$$

In this form, ETS_t, is an indicator for the announcement year of ETS pilots (2011). Therefore, the series of dummy variables, $\{\text{ETS}_{t-k}\}$, integrates the pre-announcement, announcement, and post-announcement periods. Controlling for leads allows us to examine the pre-treatment differences as a test for parallel trends. Controlling for lags enables us to trace the spillover effects in the years after the initial announcement. Note that the dummy for $k = -1$ is omitted from Equation (2) so that the estimated effects are relative to the year before the announcement (2010).

Figure 3 shows that the estimated coefficients for the leads of the ETS-announcement dummy are small in magnitude and statistically indistinguishable from zero. Hence, there is no evidence of meaningfully differential trends in firm emissions before the ETS announcement. After the announcement, we see a gradual increase in firm emissions.

[Insert Figure 3 about here]

5.2 Mechanisms

Our baseline results show that the launch of ETS pilots induces a significant increase in ETS-sister firms' total emissions. To understand the possible leakage channels, we examine the leakage effects of ETS pilots on a series of energy-related and economic characteristics. Figure 4 plots the coefficient estimates and their corresponding 95% confidence intervals.

[Insert Figure 4 about here]

Consistent with the baseline results, we find significant increases in ETS-sister firms' energy consumption, output, sales, and value-added, and the effect is generally larger during the trading phase. It suggests that ETS-regulated firms shifted their production activities to their unregulated sisters. Our analysis reveals limited impacts on ETS-sister firms' emission intensity and energy intensity. This suggests that ETS-sister firms do not actively engage in energy conservation or efficiency improvements in response to the ETS. Furthermore, we find no significant effects on their capital-labor ratio and TFP, indicating the absence of efficiency or productivity improvements among ETS-sister firms. These findings collectively indicate that the carbon leakage observed in China's ETS pilots primarily occurs through the reallocation of production activities among ETS firms rather than through efficiency gains or productivity improvements.

5.3 Heterogeneity

5.3.1 Firm Characteristics

We analyze heterogeneous effects of emission leakage across different dimensions of firm attributes. We consider both level measures (emission, energy, age, and output) and intensity measures (emission intensity, energy intensity, and TFP). To capture the firm's historical characteristics, we calculate the average of these attributes over the three years before the ETS announcement (2008-2010). This approach helps mitigate the potential bias from sample classification influenced by the treatment. We then divide the sample into two groups based on whether a firm's attribute is above or below the median value. The groups are denoted as "High" and "Low" for the respective attribute. We estimate the leakage effects separately for these two groups. Figure 5 displays the coefficient estimates and their corresponding 95% confidence intervals. The top panel presents the estimates for the announcement effect, while the bottom panel for the trading effect. This analysis allows us to examine how the leakage effects vary across different firm attribute levels.

[Insert Figure 5 about here]

Analyzing heterogeneous effects on emissions by firm characteristics reveals interesting patterns for the announcement and trading phases.[13] For level measures (emission, energy, age, and output), we observe different responses between the low and high groups of ETS-sister firms. Specifically, the low group, which includes firms that are younger or have lower carbon emissions, energy consumption, and outputs, tends to exhibit larger increases in emissions compared to the high group. This suggests that firms with lower initial levels of these attributes are more likely to experience leakage effects. However, when the group classification is based on intensity measures, such as emission and energy intensity, we do not find significant differences in carbon emissions between the low and high groups of ETS-sister firms. Furthermore, ETS-sister firms with higher productivity, as measured by TFP, tend to have larger emissions increases.

We further examine whether ETS firms' production activities are shifted towards their low-emission sister firms. Similarly, the sample is split into two groups based on whether a firm's average emission level lies above or below the median over the three years before the treatment (2008 to 2010). Figure 6 plots coefficient estimates and their corresponding 95% confidence intervals.

[Insert Figure 6 about here]

We observe a clear pattern in the heterogeneous responses of production activities between the two groups of ETS-sister firms. In the announcement phase, the low-emission group increases total output and input, while the high-emission group has no significant changes. In the trading phase, the low-emission group further invests more capital, adds labor input, and raises wages. The reallocation of production resources goes in the same direction along with carbon leakage for ETS-sister firms with low historical emissions. However, the high-emission group is relatively silent on shifting around production activities. These findings corroborate that carbon leakage occurs mainly among small ETS-sister firms.

[13]Since we use the log carbon emissions for these analyses, the results we find could be driven by the differential baseline emission level among firms in the high and low groups. Therefore, we conduct robustness checks by using carbon emissions and energy consumption as the outcome variable. The results are shown in Table A9. We winsorize or drop the observations with exceptionally high emission or energy consumption levels. Our conclusion still holds.

5.3.2 Market Performance

The variability in policy design across the ETS pilots gives rise to variations in carbon prices and allowance liquidity. In our sample period, the daily carbon price in the regional pilots ranges from \$1.38/tCO_2e to \$20.88/tCO_2e, with an average of \$5.6/tCO_2e. The average turnover rate, which represents the ratio of exchanged allowances to total allowances, is 0.018. The low carbon prices and infrequent allowance trading indicate an inactive carbon market (Zhang, Wang and Du, 2017).

To examine the heterogeneous effects of carbon prices and allowance liquidity, we introduce interaction terms between the sister-trading dummy and either the carbon price or the turnover rate in the baseline model. The estimation results are presented in Table 3. In Column (1), we find that a 1% increase in carbon price leads to a 2.2% increase in total emissions from ETS-sister firms. Similarly, Column (2) indicates that a one percentage point increase in the turnover rate is associated with a 2% increase in total emissions from ETS-sister firms. Higher carbon prices or turnover rates in the ETS pilots exert greater pressure on regulated firms, leading to stronger incentives for these firms to outsource emissions.

[Insert Table 3 about here]

5.3.3 Allowance Allocation Rules

The regional ETS pilots employ two distinct types of allowance allocation rules: mass-based and rate-based. The former focuses on regulating total emissions, while the latter targets emission intensity. The rate-based allocation rule provides an implicit subsidy for production, reducing the pressure on firms to undertake emission abatement measures (Goulder and Morgenstern, 2018; Cui et al., 2021). To investigate the heterogeneity in emission spillovers under these different allocation rules, we estimate separate baseline models for firms whose sisters are regulated by the mass-based rule and those whose sisters are regulated by the rate-based rule. The estimation results are reported in Columns (3) and (4) of Table 3. Our findings indicate that an increase in total emissions among ETS-sister firms is observed only when their corresponding ETS-regulated firms are subject to the mass-based allocation rule. This result further underscores that ETS-regulated firms primarily evade regulatory pressures by shifting production-related emissions to their unregulated sister firms, which do not directly affect emission intensities. Consequently, we do not find any evidence of emission spillovers when firms are regulated by the rate-based allowance allocation rule.

5.3.4 Where Do Emissions Go?

To examine the regional dynamics of absorbing outsourced emissions, we divide our sample based on whether firms are located in ETS regions. The estimates for these two groups are presented in the last two columns of Table 3. We find no significant impact on the carbon emissions of ETS-sister firms located in ETS regions. While these firms are not directly subject to carbon pricing regulation, the potential reallocation of production and emissions may intensify their mitigation pressure if the increased emissions push them above the ETS inclusion threshold. In contrast, we observe a positive and statistically significant effect on carbon emissions among firms in non-ETS regions. These ETS-sister firms, being exempt from ETS pressures, face fewer regulatory risks and can absorb the emissions shifted from their regulated counterparts.

To investigate whether carbon emissions are shifted towards air-polluted areas, we analyze city-level average concentrations of $PM_{2.5}$ and SO_2 as proxies for air pollution, along with corresponding exposure data during the pre-ETS period (2007-2010). We divide the sample based on the median values of these air quality measures, creating the "Low" and "High" dummies, indicating concentrations or exposure below or above the median. We introduce interaction terms between the ETS-sister dummy, ETS phase indicators, and air quality proxies in our regression model. The results are presented in Table 4, with columns varying by the air pollution measures.

[Insert Table 4 about here]

Consistently, the coefficient estimates for the interaction terms with the "Low" dummy are positive and statistically significant during both the announcement and trading phases, exhibiting larger magnitudes than those interacting with the "High" dummy. These findings suggest that carbon emissions are primarily shifted towards ETS-sister firms in less air-polluted areas. One plausible interpretation is that ETS-regulated firms aim to mitigate additional regulatory risks. Since air pollutants are often co-emitted with carbon emissions, less-polluted areas may have less stringent environmental regulations compared to more-polluted areas. By redirecting carbon emissions towards less-polluted areas, ETS firms can potentially avoid additional compliance pressures imposed by other environmental regulations.

5.4 Robustness Checks

We perform an extensive array of robustness checks to ensure the validity and reliability of our findings. These checks encompass various aspects, including the definition of unregulated firms, potential confounding factors, alternative matching methods, emission measurement, and different treatment timing.

[Insert Figure 7 about here]

Narrowed Definition of Unregulated Firms. Our primary analyses categorize a firm as unregulated if it is not included in the government-issued ETS firm list. However, a potential concern arises regarding subsidiaries of ETS firms, as they could also fall under the purview of the ETS. Certain ETS-sister firms could be affected by their parent company's ETS status. To address this concern, we conduct an additional analysis by excluding firms whose parent companies are regulated by the ETS, providing a more focused examination of carbon leakage. Furthermore, as an extra robustness check, we exclude firms whose highest recorded carbon emissions within our sample period surpass the ETS regulation threshold, as indicated in Table A1. These additional analyses allow us to assess the robustness of our findings and ensure that our results are not driven by the inclusion of subsidiaries or firms approaching the ETS regulation threshold.

Confounding Factors. Common shocks at the regional or industry level can introduce confounding factors that may influence our identification of spillover effects. To address this concern, we account for these common shocks by including province-year and industry-year fixed effects in our analysis. However, we acknowledge the presence of other firm-level environmental or energy policies that could potentially confound our results.

During our sample period, the Chinese government implemented stringent air pollution control policies targeting the Beijing, Tianjin, and Hebei (BTH) area, which overlaps with some ETS pilot regions. To ensure the robustness of our findings, we conduct a sensitivity analysis by excluding firms located in the BTH area and re-estimate our model. By doing so, we can examine whether the observed leakage effects hold when controlling for the effects of these local air pollution control policies.

Furthermore, we address the potential influence of the Top 10,000 Energy Saving (ES10k) program, which imposes energy-saving targets on energy-intensive manufacturing firms. To account for the ES10k program, we employ two measures: (i) a binary variable indicating whether the firm is regulated by the ES10k, and (ii) a binary variable indicating whether the firm itself or its sister entities are regulated by the ES10k. We also perform an additional robustness check by excluding firms that are regulated by the ES10k or have regulated sister entities and re-estimate the baseline model. This allows us to examine the robustness of our results on the potential influence of the ES10k program on carbon leakage.

Alternative Matching Covariates. In our baseline model, we employ Mahalanobis distance-based matching, utilizing two covariates that are crucial indicators of a firm's regulatory status in a pilot region: total emissions and emission intensity. These covariates capture the key determinants of a firm's emissions and their intensity relative to their output. However, to ensure the robustness of our main results, we explore alternative sets of matching covariates, including (i) total emissions and output, (ii) energy consumption and output, and (iii) total emissions, emission intensity, and energy consumption.

Alternative Matching Units. To address concerns regarding the small sample size resulting from one-to-one nearest-neighbor matching, we conduct additional robustness checks using alternative matching algorithms that provide a larger sample size. Specifically, we consider one-to-two and one-to-three nearest neighbor matching while maintaining the same set of covariates used in the baseline model (i.e., total emissions and emission intensity).

Alternative Emission Measures. The data of natural gas consumption is not of high quality. To address the issue of missing values in natural gas consumption and potential measurement errors in carbon emissions, we implement two approaches in our analysis. First, we consider excluding natural gas consumption from calculating carbon emissions. Second, we conduct an alternative analysis to exclude firms with non-zero natural gas consumption.

Product Similarity. To address concerns regarding potential differences in business scopes between ETS-regulated firms and their unregulated sisters, we collect information on product categories for both types of firms. We posit that the production of similar products within the same category is more likely to be substitutable across firms. We find that over 80% of ETS-sister firms share the same product category as their corresponding ETS-regulated firms. This high level of overlap supports the substitutability of production activities within these shared product categories. To further strengthen our argument, we exclude ETS-sister firms whose products do not belong to the same category as those produced by their corresponding ETS-regulated firms.[14] By excluding these firms, we ensure a more homogeneous sample with a closer alignment in product categories between ETS firms and their unregulated sisters.

Separate Estimates for Different Timing Groups. To address concerns about potential estimation bias arising from variations in the start time of trading, we analyze the baseline model and event study model separately for different timing groups following Goodman-Bacon (2021). Specifically, we focus on unregulated firms whose regulated sisters began trading in either 2013 or 2014.[15] This approach ensures that the comparison is made exclusively between control firms and treated firms that entered the trading phase at the same time, thereby minimizing potential bias introduced by differential timing. Additionally, we run regressions that combine the announcement and trading phases by employing a one-time indicator for the post-2010 period. The results are shown in Table A6 and Figure A1.

Overall, our baseline conclusions survived all these robustness checks. By systematically examining these factors, we enhance the robustness and generalizability of our results, providing a more comprehensive understanding of the dynamics at play in the context of carbon leakage and the effectiveness of the ETS pilots.

5.5 Aggregate Effect of ETS Pilots

To gain a comprehensive understanding of the aggregate effect of ETS pilots on firm emissions, we extend our analysis by estimating a modified version of the baseline model. This variant takes into account the effects on both regulated firms and their unregulated sisters, allowing us to capture the overall impact of ETS pilots on emissions. In this analysis, we consider all ETS-regulated firms and their sisters as the treatment group. To construct the control group, we follow the same matching

[14] Among 5,552 observations in the baseline, this robustness check drops 557 ones.

[15] Since we perform a one-to-one matching, each ETS-sister firm is paired with an unrelated control firm. Therefore, we run separate regressions for the treated firms in different timing groups, using their respective matched firms as controls.

procedure as before, ensuring that the control firms are well-matched to the treatment group based on relevant covariates. Using this matched sample, we estimate the baseline specification, but with a modification. Instead of using the sister dummy variable, we introduce an ETS group dummy variable that takes a value of one for ETS-regulated firms and their sisters. This revised specification enables us to examine the combined effect of ETS pilots on both regulated firms and their unregulated sisters.

Table 5 presents the estimation results for the aggregate effect of ETS pilots on firm emissions. Our findings indicate a positive and statistically significant impact during the announcement period. Specifically, according to Column (1), there is an average increase of 6.6% in total emissions among both ETS firms and their sisters. We also observe a slight increase in energy consumption and output. Although the coefficient estimates for total emissions, energy consumption, and output remain positive, they are not statistically significant during the trading period. In addition, we do not find any significant effects on intensity measures.

These results suggest that the unintended emission spillovers significantly diminish the effectiveness of ETS pilots in reducing carbon emissions. It appears that carbon regulation under the ETS pilots leads to a redistribution of carbon emissions across firms rather than a reduction in nationwide emissions. It is important to acknowledge the limitations of this estimated aggregate effect, as we can only capture emissions within the conglomerates that appeared in our sample. There may be instances of carbon leakage occurring outside firm ownership networks or in other firms, which we are unable to account for in our analysis.

[Insert Table 5 about here]

6 Conclusion

The carbon ETS plays a crucial role in achieving the global climate target, but its effectiveness is threatened by the risk of carbon leakage. Drawing on the variations in policy stringency across China's regional ETS pilots, this study utilizes comprehensive firm ownership networks to investigate emission leakage and corresponding economic adjustment. Our findings provide unequivocal evidence of emission leakage resulting from carbon pricing, in which ETS-regulated firms shift their emissions to their unregulated sister entities within the same ownership network.

Despite previous evidence of a 16.7% reduction in carbon emissions for ETS-regulated firms compared to unregulated ones (Cui et al., 2021), our study reveals a 8.3% increase in carbon emissions for unregulated firms that are sisters of ETS-regulated firms. Mechanism analyses further uncover that carbon leakage is accompanied by the reorganization of production resources within the firm ownership network, particularly among firms regulated under the mass-based allocation rule. Carbon emissions primarily shift towards ETS-sister firms with lower baseline emission levels, located in non-ETS regions, or free from other environmental policy pressures.

These findings carry significant implications for the design of carbon ETS and the implementation of carbon tariffs to effectively achieve mitigation targets and mitigate potential leakage risks. Our results demonstrate that conglomerates respond to carbon pricing by adjusting production resources and carbon emissions within the ownership networks. The awareness of such carbon leakage highlights the challenges in designing and evaluating carbon pricing mechanisms. An optimal carbon policy should consider the potential channels of leakage through which regulated firms may evade compliance. Furthermore, it underscores the need for a comprehensive assessment of ETS effects within a general equilibrium framework.

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Figures and Tables

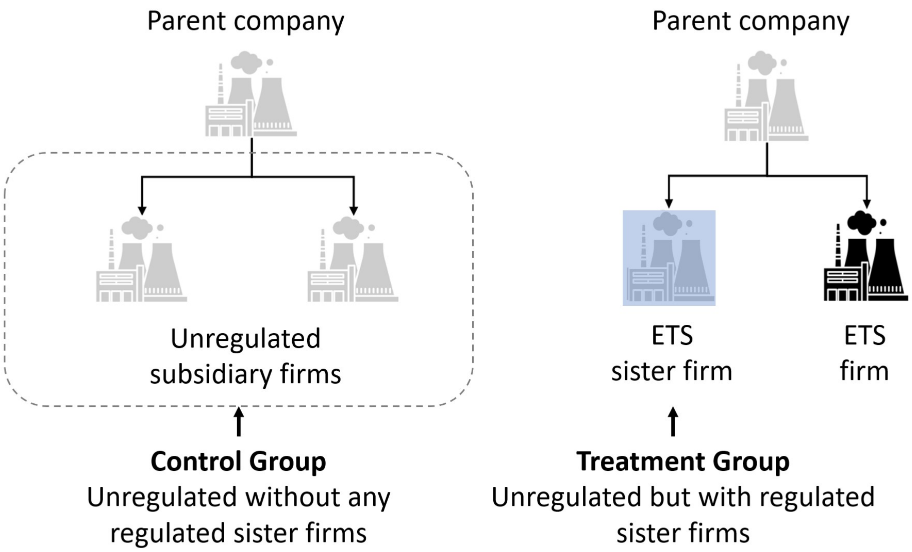

Figure 1: Definition of the Treatment and Control Groups

Notes: The graph illustrates how we define the treatment and control groups. The black arrow means that a firm owns or invests in another firm. ETS firms are in black while unregulated firms are in gray. The blue one represents ETS-sister firms, i.e., an unregulated firm owned by the same conglomerate as an ETS firm. The circled ones are unrelated firms, i.e., firms whose ownership network does not have any ETS entities.

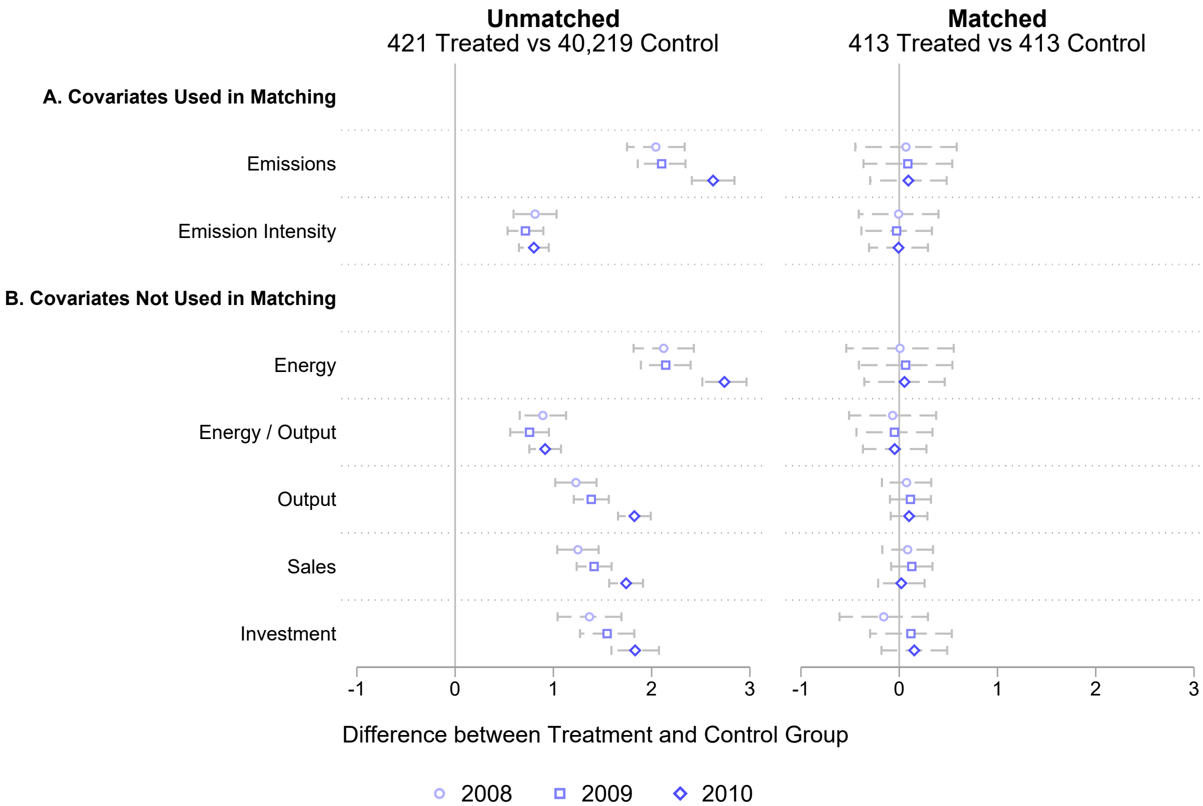

Figure 2: Balancing Test

Notes: The figure compares a series of firm characteristics between the treatment and control groups separately for the unmatched and matched sample. All variables are measured in logarithms. The mean differences and their corresponding 95% confidence intervals are plotted.

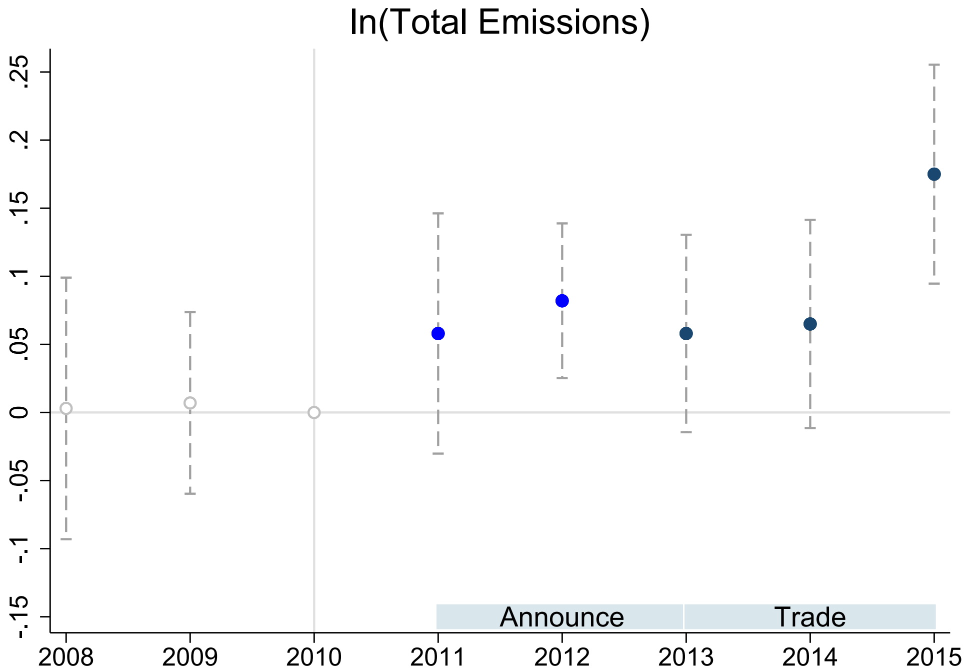

Figure 3: Event Study Estimates of the Spillover Effect

Notes: Figure plots coefficients and their 95% confidence intervals from an event-study model that estimates the dynamic effect of China's ETS pilots on ETS-sister firms' total emissions. The outcome variable is measured in logarithms. The regression controls for the firm, province-year, and industry-year fixed effects. One year before the announcement of the ETS (i.e., t = 2011) is omitted from the regression and considered as the reference group. The standard errors are clustered at the industry level. The corresponding estimation results are presented in Table A5.

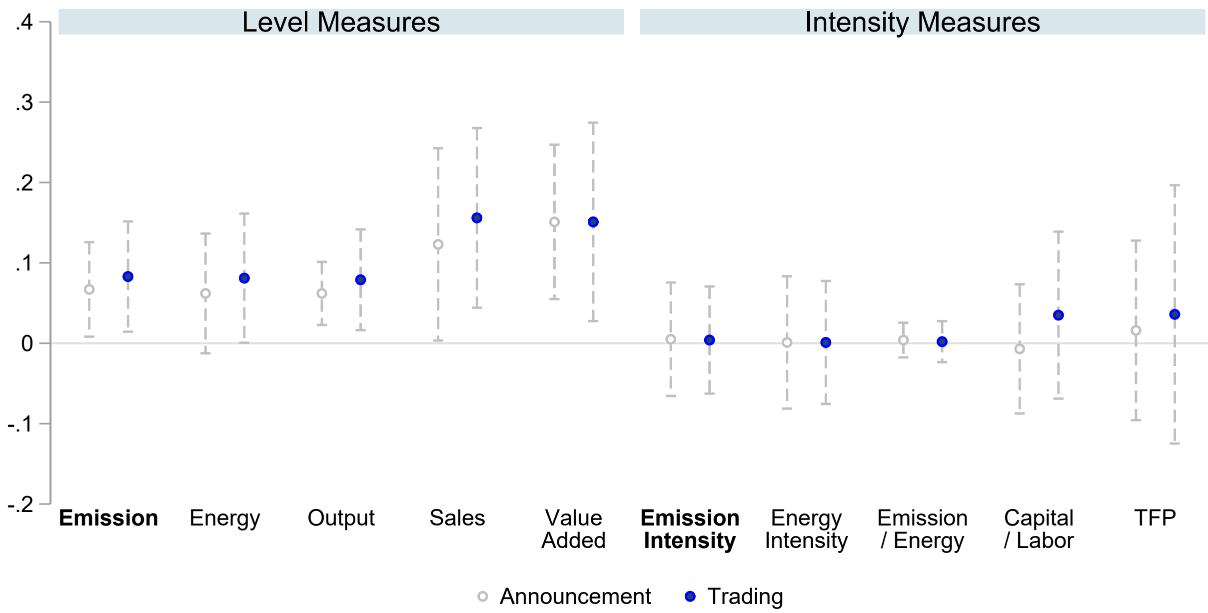

Figure 4: Effects on ETS-Sister Firms' Level and Intensity Measures

Notes: Figure plots coefficient estimates and their corresponding 95% confidence intervals of Equation (1) that studies the effects of China's ETS pilots on ETS-sister firms' level and intensity measures for energy consumption and economic activities. The dependent variables (indicated by the y axis) are in logarithms. All regressions control firm, province-year, and industry-year fixed effects. The standard errors are clustered at the industry level. The corresponding estimation results are presented in Table A7.

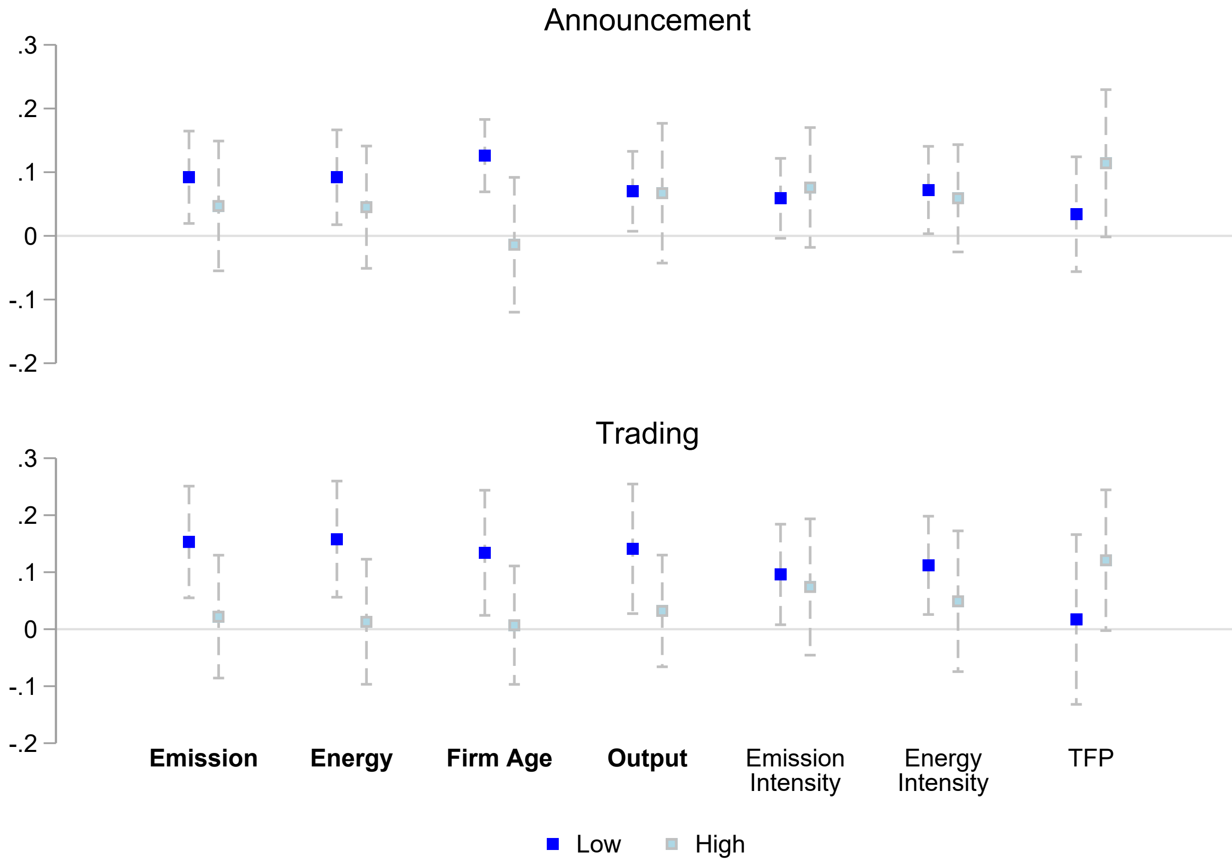

Figure 5: Heterogeneous Effects on Emissions by Firm Characteristics

Notes: Figure plots coefficient estimates and their corresponding 95% confidence intervals. The outcome variable is the logarithm of the firm's total emission. The top panel shows the estimates for the announcement effect and the bottom panel shows the estimates for the trading effect. We estimate these effects on firm emissions separately by different firm characteristics (indicated by the horizontal axis). Here, we split our sample based on whether a firm's attribute is below (indicated by Low) or above (indicated by High) the median in the three-year observation prior to the ETS. The corresponding estimation results are presented in Table A8.

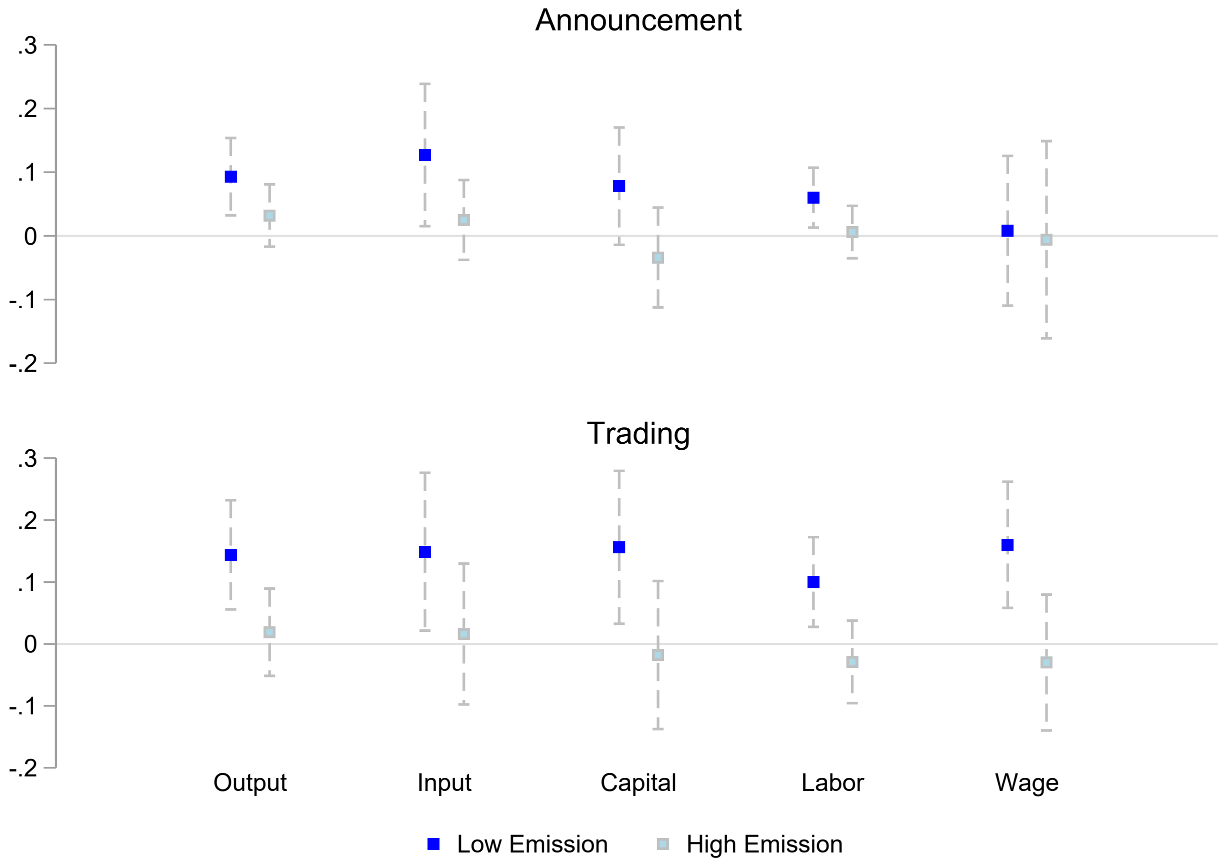

Figure 6: Heterogeneous Effects on Production Activities by Pre-ETS Emission Levels

Notes: Figure plots coefficient estimates and their corresponding 95% confidence intervals. The outcome variables (indicated by the horizontal axis) are measured in logarithms. The top panel shows the estimates for the announcement effect and the bottom panel shows the estimates for the trading effect. We estimate these effects separately by firms' pre-ETS emission levels. Here, we split our sample based on whether a firm's carbon emission is below (indicated by Low) or above (indicated by High) the median in the three-year observation prior to the ETS. The corresponding estimation results are presented in Table A10.

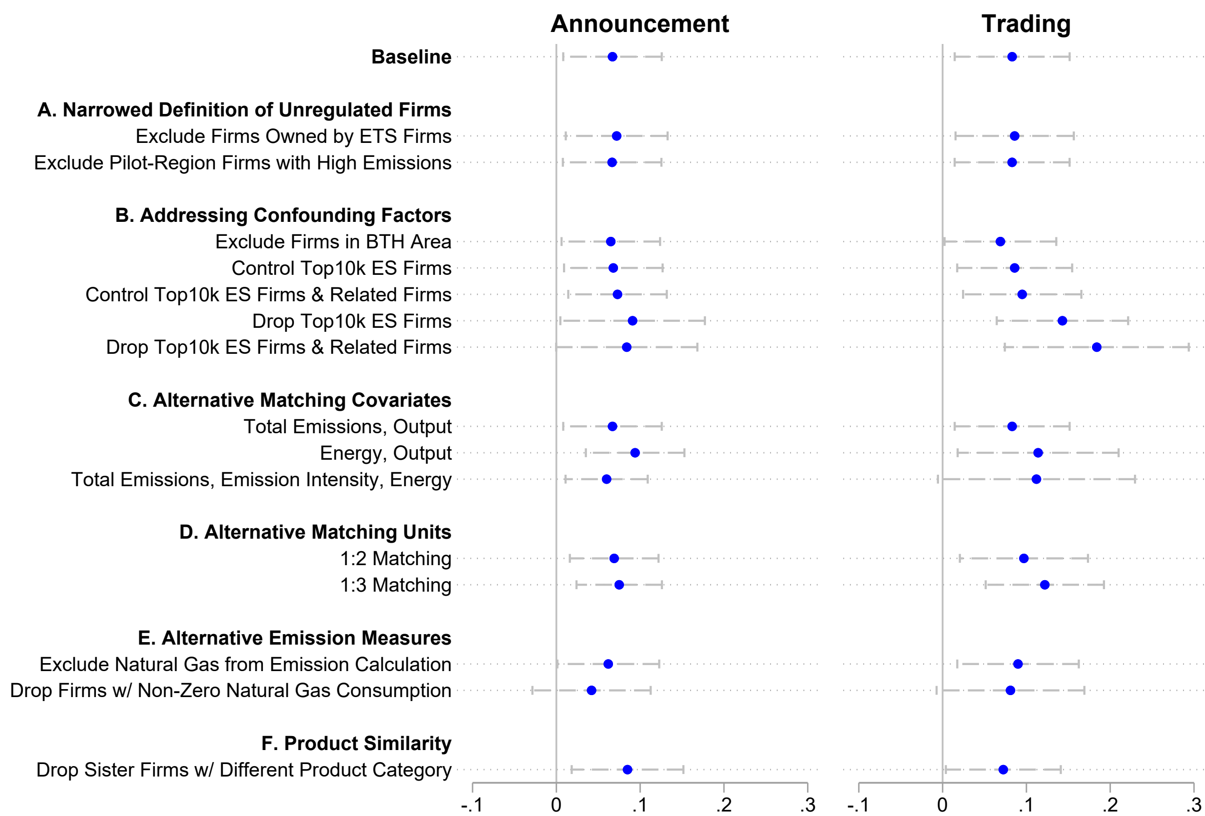

Figure 7: Robustness Checks

Notes: The figure plots the coefficient estimates from a series of regression models as robustness checks. Each row represents a specific model specification. The first row replicates the estimates from our baseline model, i.e., column (3) of Table 2. Panel A applies narrow definitions of unregulated firms by (i) excluding firms owned by ETS firms; (ii) excluding firms with emissions above the threshold of the corresponding pilot region as listed in Table A1. Panel B addresses confounding factors by (i) excluding firms located in the Beijing-Tianjin-Hebei area; (ii) adding a control variable indicating whether the firm itself has been regulated by the "Top 10,000" Energy Savings Program; (iii) adding a control variable indicating whether the firm itself or its sisters have been regulated by the "Top 10,000" Energy Savings Program; (iv) excluding firms regulated by the "Top 10,000" Energy Savings Program; (v) excluding firms if they or their sisters are regulated by the "Top 10,000" Energy Savings Program. In Panel C, we perform the matching based on alternative sets of covariates. In Panel D, we use 1-to-2 or 1-to-3 nearest matching. In Panel E, we use two alternative carbon emission measures to address concerns about the completeness of natural gas consumption data: (i) excluding natural gas from emission calculation; (ii) dropping firms with non-zero natural gas consumption. In Panel F, we drop unregulated sister firms whose products are not in the same category as those produced by the ETS-regulated firms. All regressions control firm, province-year, and industry-year fixed effects. Standard errors in parentheses are clustered at the industry level.

Table 1: Summary Statistics

Variable	N	Mean	S.D.	Min.	Max.
A. Firm Emission and Energy Consumption					
Emissions	5,555	9.868	2.800	2.180	17.390
Emission Intensity	5,555	-0.440	2.187	-7.686	5.795
Energy	5,555	8.500	2.943	0.206	15.890
Energy / Output	5,555	-1.808	2.348	-9.674	4.763
B. Firm Economic Characteristics					
Output	5,555	10.310	1.338	5.868	14.660
Value Added	5,325	8.632	1.483	-2.303	13.090
Sales	5,525	10.400	1.405	0.095	14.740
Labor	5,555	5.892	1.117	0.000	9.665
Wage	5,479	7.351	1.313	-2.303	11.600
Capital	5,008	9.434	1.694	1.259	17.130
Investment	4,537	6.407	2.280	-2.520	13.440
Export	5,555	2.509	4.006	0.000	13.670
TFP	4,608	-0.326	1.227	-4.476	5.396
Capital / Labor	5,008	3.567	1.494	-2.455	10.650
Output / Labor	5,555	4.416	1.048	0.810	11.290
Output / Capital	5,008	0.820	1.117	-4.435	6.501
C. Carbon Market Performance					
Carbon Price	5,555	0.655	1.434	0.000	4.355
Turnover Rate	5,555	0.003	0.010	0.000	0.056

Notes: Panels A and B provide summary statistics of firm-level carbon emissions, energy consumption, and economic attributes. Panel C provides summary statistics of carbon market performance. All variables except for turnover rate are measured in logarithms. Units: emissions – $MtCO_2$; energy consumption – metric tons of standard coal equivalent (TCE), with 1 TCE = 29,307 GJ; output, value-added, sales, wage, capital, investment, export – 10^4 RMB; labor – the number of employees; carbon price – RMB. Turnover rate is the ratio of trading volume to the total allowance in each carbon market.

Table 2: Spillover Effects on Firm Emissions

Dep Var: ln(Total Emissions)	(1)	(2)	(3)
Sister × Announcement	0.072***	0.069**	0.067**
	(0.020)	(0.025)	(0.030)
Sister × Trading	0.092**	0.092***	0.083**
	(0.042)	(0.031)	(0.035)
Firm FE	✓	✓	✓
Year FE	✓	✓	
Province Trend		✓	
Industry Trend		✓	
Province-Year FE			✓
Industry-Year FE			✓
Observations	5,555	5,555	5,552

Notes: Table shows estimates of Equation (1). Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Heterogeneous Effects by Policy Features

Dep Var:	Market Performance		Allocation Rule		Firm Location	
	Carbon Price	Allowance Liquidity	Mass Based	Rate Based	ETS Pilots	Other Regions
ln(Total Emissions)	(1)	(2)	(3)	(4)	(5)	(6)
Sister × Announcement	0.065*	0.044	0.080**	0.016	0.024	0.083**
	(0.033)	(0.035)	(0.037)	(0.039)	(0.060)	(0.036)
Sister × Trading × Price	0.022**					
	(0.010)					
Sister × Trading × Turnover		2.021*				
		(1.120)				
Sister × Trading			0.105**	0.037	0.076	0.079
			(0.049)	(0.060)	(0.106)	(0.054)
Firm FE	✓	✓	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓
Observations	5,524	5,524	2,624	2,858	1,387	4,084

Notes: Table shows heterogeneous effects on total emissions by allowance allocation rules and firm characteristics. Columns (1) and (2) present estimates for carbon prices and turnover rates. Columns (3) and (4) present estimates based on firms whose sisters are regulated by the ETS under the mass-based vs the rate-based allocation rule. Columns (5) and (6) present estimates for firms located within and outside the ETS pilot regions. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by the parent company of an ETS firm. Announcement an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Heterogeneous Effects on Emissions by City Air Pollution Exposure

	Dep. Var.: ln(Emissions)			
Sample split by:	Concentration		Exposure	
	$PM_{2.5}$	SO_2	$PM_{2.5}$	SO_2
	(1)	(2)	(3)	(4)
Sister × Announcement × Low	0.080*	0.094**	0.087*	0.104**
	(0.045)	(0.044)	(0.051)	(0.044)
Sister × Announcement × High	0.058	0.047	0.047	0.025
	(0.039)	(0.048)	(0.040)	(0.039)
Sister × Trading × Low	0.113**	0.109*	0.111**	0.119**
	(0.050)	(0.063)	(0.050)	(0.056)
Sister × Trading × High	0.078	0.084*	0.051	0.035
	(0.055)	(0.044)	(0.058)	(0.060)
Firm FE	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓
Observations	5,489	5,489	5,367	5,367

Notes: The table reports estimated effects separately by city-level pre-ETS air quality. Here, we split our sample by the median of city-level average $PM_{2.5}$ and SO_2 concentrations and their corresponding population exposure over the pre-ETS period (2007-2010). Population exposure is calculated by multiplying $PM_{2.5}$ or SO_2 concentrations with the city population. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Regressions include firm, industry-year, and province-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Aggregate Effect of ETS Pilots

Dep. Var. (in logs)	Total Emissions (1)	Energy (2)	Output (3)	Emission Intensity (4)	Energy/ Output (5)	Emission/ Energy (6)
ETS × Announcement	0.066**	0.068*	0.056**	0.010	0.013	-0.002
	(0.032)	(0.036)	(0.022)	(0.035)	(0.039)	(0.009)
ETS × Trading	0.043	0.055	0.050	-0.007	0.005	-0.012
	(0.041)	(0.048)	(0.031)	(0.033)	(0.040)	(0.012)
Firm FE	✓	✓	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓
Observations	9,202	9,202	9,202	9,202	9,202	9,202

Notes: ETS is an indicator for ETS firms and their unregulated sisters. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ONLINE APPENDIX

Carbon Leakage within Firm Ownership Networks

Jingbo Cui   Chunhua Wang   Zhenxuan Wang   Junjie Zhang   Yang Zheng

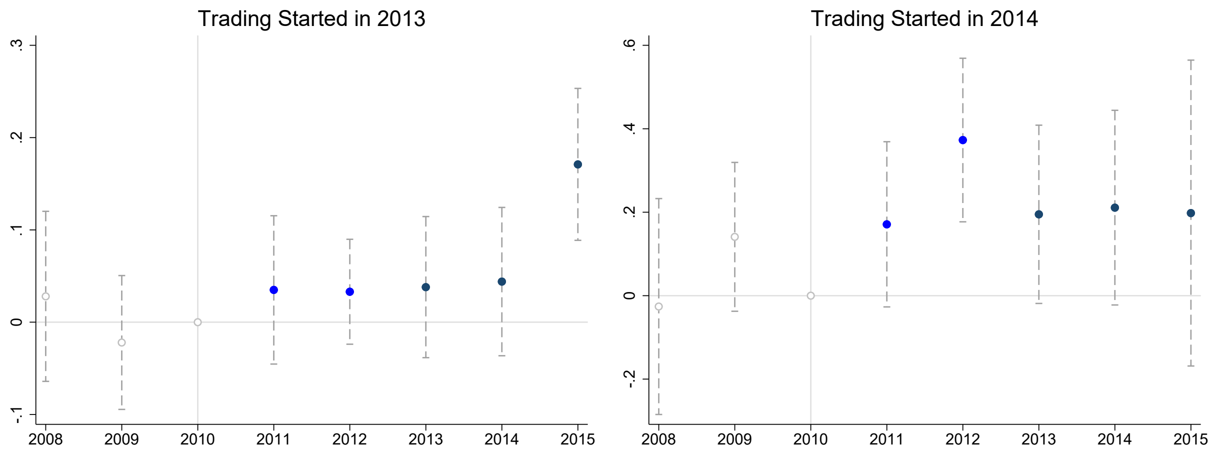

Figure A1: Event Study Estimates by Different Timing Group

Notes: Figure plots coefficients and their 95% confidence intervals from an event-study model that estimates the dynamic effect separately for two groups of firms whose sisters started trading in 2013 (the left panel) and 2014 (the right panel). The outcome variable is measured in logarithms. The regression controls for the firm, province-year, and industry-year fixed effects. One year before the announcement of the ETS (i.e., t = 2010) is omitted from the regression and considered as the reference group. The standard errors are clustered at the industry level.

Table A1: Covered Sectors across Regional ETS Pilots

Region	Announcement Year	Launch Year	Covered Sectors	Threshold	Emissions Covered
Beijing	2011	2013	Electricity, heating, cement, petrochemical, and other industries, large public buildings including hospitals, schools and governments	>10kt	40%
Shanghai	2011	2013	Electricity, iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textile, aviation, airports and ports, public and office buildings, railway stations	Industries>20kt; Non-industries>10kt	57%
Shenzhen	2011	2013	Electricity, building, manufacturing, water supply	Industries>5kt; Public buildings>20km^2 Office buildings>10km^2	40%
Guangdong	2011	2013	Electricity, cement, iron and steel, petrochemical industries, public services including hotels, restaurants and businesses	2013: >20kt; Since 2014: industries>10kt; non-industries>5kt	58%
Tianjin	2011	2013	Electricity, heating, iron and steel, chemical and petrochemical industries, oil and gas exploration	>20kt	60%
Hubei	2011	2014	Electricity, heating, metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement, medicine and pharmacy, food and beverage, papermaking	energy consumption>60k tce	33%
Chongqing	2011	2014	Electricity, metallurgy, chemical industries, cement, iron and steel	>20kt	39.5%

Source: Table S1 in the SI Appendix in Cui et al. (2021).

Table A2: Allowance Allocation across Regional ETS Pilots

Region	Mass-based System				Rate-based System	
	Emission-based grandfathering, fixed baseline periods[1]	Emission-based grandfathering, moving baseline periods[2]	Fixed historical production based benchmarking[3]	Moving historical production based benchmarking[4]	Intensity-based grandfathering[5]	Current production based benchmarking[6]
	Exogenous	Endogenous (output-based)	Exogenous	Endogenous (output-based)	Endogenous (output-based)	Endogenous (output-based)
Beijing	Cement, petrochemical and other industries, large public buildings including hospitals, schools and governments.				Electricity, heating	
Shanghai	Iron and steel, petrochemical and chemical industries, metallurgy, building materials, paper making, textiles, public and office buildings, railway stations					Electricity, aviation, airports and ports.
Shenzhen					Manufacturing	Electricity, heating, building, water supply.
Guangdong[7]		Electricity (cogeneration genset), cement (cement mining and other grinding processes), steel (DR-EAF route), petrochemical industries.				Electricity (pure genset), cement (cement clinker production and cement grinding process), steel (BF-BOF route).
Tianjin	Iron and steel, chemical and petrochemical industries, oil and gas exploration.				Electricity, heating	
Hubei		Metallurgy, iron and steel, automobile and equipment, chemical and petrochemical industries, cement (only 2014), medicine and pharmacy, food and beverage, paper making.				Electricity, heating, cement (only 2015).
Chongqing[8]		Electricity, metallurgy, chemical industries, cement, iron and steel (due to self-declaration & ex-post adjustment).				

Source: Table S2 in the SI Appendix in Cui et al. (2021).
Notes: 1. Emission-based grandfathering with fixed baseline periods, known as "pure grandfathering", depends on the firm's historical emission level in fixed periods to compute the number of allowances.
2. Since the baseline periods of a firm's historical emissions are moving, the number of allowances is updated based on outputs across periods and therefore categorized as "output-based" allocation.
3. Allowance = sectoral benchmark × firms' historical production in fixed baseline periods.
4. Allowance = sectoral benchmark × firms' historical production in moving baseline periods. Hence, the number of allowances is updated based on output values across periods and categorized as "output-based" allocation.
5. Intensity-based grandfathering depends on a firm's historical emission intensity level and the firm's current output level to compute the number of allowances.
6. Allowance = sectoral benchmark × firms' current production level.
7. The Guangdong pilot determines allowance allocation methods based on industrial processes and techniques in the electricity, cement, and steel sectors.
8. The Chongqing pilot allocates allowances based on the self-declaration number by covered firms and allows for ex-post adjustment of the allowance number at the end of the compliance period.

Table A3: China's CO_2 Emission Factors

Energy	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

Source: Table S3 in the SI Appendix in Cui et al. (2021).
Notes: 1. China has six regional power grids whose carbon emission factors are computed separately. The North China Grid covers Beijing, Tianjin, Hebei, Shandong, Shanxi, and Inner Mongolia. The Northeast China Grid covers Liaoning, Jilin, and Heilongjiang. The East China Grid covers Shanghai, Jiangsu, Zhejiang, Anhui, and Fujian. The Central China Grid covers Henan, Hubei, Hunan, Jiangxi, Chongqing, and Sichuan. The Northwest China Grid Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The China Southern Power Grid covers Guangdong, Guangxi, Yunnan, Guizhou, and Hainan.
2. Source of Panel A: Department of Energy Statistics, National Bureau of Statistics of China and IPCC Guidelines for National Greenhouse Gas Inventories.
3. Source of Panel B: National Center for Climate Change Strategy and International Cooperation, National Development and Reform Commission of China.

Table A4: Balancing Test

Variables (in log)	Year	Unmatched			Matched		
		Treated (1)	Control (2)	P-value (3)	Treated (4)	Control (5)	P-value (6)
A. Covariates Used in Matching							
Emissions	2008	10.052	8.009	0.000	10.087	10.018	0.794
	2009	10.062	7.960	0.000	10.085	9.997	0.703
	2010	9.785	7.159	0.000	9.801	9.708	0.638
Emission Intensity	2008	-0.200	-1.014	0.000	-0.175	-0.169	0.977
	2009	-0.226	-0.941	0.000	-0.209	-0.182	0.886
	2010	-0.477	-1.279	0.000	-0.475	-0.468	0.964
B. Covariates Not Used in Matching							
Energy	2008	8.654	6.531	0.000	8.689	8.682	0.978
	2009	8.686	6.542	0.000	8.708	8.643	0.787
	2010	8.376	5.635	0.000	8.392	8.338	0.797
Energy / Output	2008	-1.598	-2.492	0.000	-1.572	-1.505	0.766
	2009	-1.602	-2.360	0.000	-1.585	-1.536	0.806
	2010	-1.886	-2.802	0.000	-1.884	-1.838	0.779
Output	2008	10.252	9.023	0.000	10.262	10.187	0.559
	2009	10.288	8.902	0.000	10.293	10.179	0.284
	2010	10.262	8.437	0.000	10.276	10.176	0.293
Sales	2008	10.317	9.067	0.000	10.328	10.242	0.516
	2009	10.324	8.909	0.000	10.330	10.202	0.232
	2010	10.219	8.479	0.000	10.235	10.213	0.857
Investment	2008	6.562	4.729	0.000	6.566	6.413	0.368
	2009	6.688	5.141	0.000	6.701	6.582	0.575
	2010	6.602	5.234	0.000	6.598	6.756	0.492
# Firms		413	40,219		413	413	

Notes: Firm-level attributes used in the matching procedure are historical records in 2008, 2009, and 2010 prior to the announcement of ETS pilots. Variables listed in this table are in logarithms.

Table A5: Event-Study Model Estimates

Dep Var (in log)	(1) Total Emissions
Sister × ETS (k=-3)	0.003
	(0.049)
Sister × ETS (k=-2)	0.007
	(0.034)
Sister × ETS (k=0)	0.058
	(0.045)
Sister × ETS (k=1)	0.082***
	(0.029)
Sister × ETS (k=2)	0.058
	(0.037)
Sister × ETS (k=3)	0.065
	(0.039)
Sister × ETS (k=4)	0.175***
	(0.041)
Firm FE	✓
Province-Year FE	✓
Industry-Year FE	✓
Observations	5,554

Notes: Table reports event-study model estimates plotted in Figure 3. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. ETS($k = 0$), is an indicator for the announcement year of ETS pilots (i.e., 2011). The dummy indicating one-year prior to the ETS announcement is omitted from the regression and considered as the reference. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Robustness Checks on Different Timing Groups

Dep Var: ln(Total Emissions)	Whole Sample	By Timing Group			
		2013		2014	
	(1)	(2)	(3)	(4)	(5)
Sister × Post Announcement	0.075**	0.053**		0.187*	
	(0.028)	(0.025)		(0.107)	
Sister × Announcement			0.035		0.199*
			(0.029)		(0.099)
Sister × Trading			0.068**		0.167
			(0.033)		(0.136)
Observations	5,552	4,401	4,401	1,094	1,094

Notes: In column (1), we use the whole sample. In columns (2) - (5), we estimate our baseline model in Equation (1) separately for the matched control firms and the treatment firms whose sisters started trading in 2013 and 2014. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Post Announcement is an indicator for the post-announcement period of the ETS pilots (i.e., after 2010). Announcement is an indicator for the announcement period of the ETS pilots. Trading is an indicator of the trading period of the ETS pilots. All regressions include firm, province-year, and industry-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Effects on Firm Energy Consumption and Economic Activities

Dep. Var. (in log)	Total Emissions	Energy	Output	Sales	Value Added
	(1)	(2)	(3)	(4)	(5)
Sister × Announcement	0.067**	0.062	0.062***	0.123*	0.151***
	(0.030)	(0.038)	(0.020)	(0.061)	(0.049)
Sister × Trading	0.083**	0.081*	0.079**	0.156**	0.151**
	(0.035)	(0.041)	(0.032)	(0.057)	(0.063)
Observations	5,552	5,552	5,552	5,522	5,313
Dep. Var. (in log)	Emission Intensity	Energy/ Output	Emission/ Energy	Capital/ Labor	TFP
	(8)	(9)	(10)	(11)	(12)
Sister × Announcement	0.005	0.001	0.004	-0.007	0.016
	(0.036)	(0.042)	(0.011)	(0.041)	(0.057)
Sister × Trading	0.004	0.001	0.002	0.035	0.036
	(0.034)	(0.039)	(0.013)	(0.053)	(0.082)
Observations	5,552	5,552	5,552	4,998	4,590

Notes: Table reports coefficient estimates plotted in Figure 4. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Regressions include firm, industry-year, and province-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Heterogeneous Effects on Emissions by Firm Characteristics

	Dep. Var.: ln(Emission)						
by Pre-ETS Level of:	Emission	Energy	Firm Age	Output	Emission Intensity	Energy Intensity	TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sister × Announcement × Low	0.092**	0.092**	0.126***	0.070**	0.059*	0.072*	0.034
	(0.037)	(0.038)	(0.029)	(0.032)	(0.032)	(0.035)	(0.046)
Sister × Announcement × High	0.047	0.045	-0.014	0.067	0.076	0.059	0.114*
	(0.052)	(0.049)	(0.054)	(0.056)	(0.048)	(0.043)	(0.059)
Sister × Trading × Low	0.153***	0.158***	0.134**	0.141**	0.096**	0.112**	0.017
	(0.050)	(0.052)	(0.056)	(0.058)	(0.045)	(0.044)	(0.076)
Sister × Trading × High	0.022	0.013	0.007	0.032	0.074	0.049	0.121*
	(0.055)	(0.056)	(0.053)	(0.050)	(0.061)	(0.063)	(0.063)
Observations	5,552	5,552	5,461	5,552	5,552	5,552	4,697

Notes: Table reports coefficient estimates plotted in Figure 5. The outcome variable is the firm's total emission measured in logarithms. In each column, we estimate these effects on firm emissions separately by terciles of different firm characteristics (indicated by the horizontal axis). Here, we split our sample by the lower (indicated by Low) and upper tercile (indicated by High) of different variables. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Regressions include firm, industry-year, and province-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Heterogeneous Effects on Levels of Emission and Energy Consumption

Dep Var (in levels)	Emission		Energy	
	Winsorize (1)	Trim (2)	Winsorize (3)	Trim (4)
Sister × Announcement × Low	2,205.992**	2,656.365***	486.291*	529.989**
	(865.704)	(779.431)	(283.089)	(205.153)
Sister × Announcement × High	-2,513.554	-2,510.168	-631.789	-545.997
	(2,656.190)	(3,032.768)	(821.969)	(1,050.806)
Sister × Trading × Low	2,367.617*	2,422.962**	445.389	437.325
	(1,327.799)	(1,050.727)	(423.057)	(283.569)
Sister × Trading × High	-6,152.054*	-2,049.155	-2,056.989*	1.179
	(3,451.830)	(3,278.102)	(1,108.607)	(887.915)
Observations	5,552	4,530	5,552	4,528

Notes: The outcome variable is the firm's total emission and energy consumption measured in raw levels. In columns (1) and (3), we winsorize the top 1,000 values of the emission outcome. In columns (2) and (4), we trim the top 1,000 values of the emission outcome. In each column, we estimate these effects on firm emissions separately by terciles of pre-ETS emission levels. Here, we split our sample by the lower (indicated by Low) and upper tercile (indicated by High) of pre-ETS emission levels. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Regressions include firm, industry-year, and province-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Heterogeneous Effects on Production Activities by Pre-ETS Emission Levels

Dep. Var. (in log)	Output	Input	Capital	Labor	Wage
by Emission Levels	(1)	(2)	(3)	(4)	(5)
Sister × Announcement × Low	0.093***	0.127**	0.078	0.060**	0.008
	(0.031)	(0.057)	(0.047)	(0.024)	(0.060)
Sister × Announcement × High	0.032	0.025	-0.034	0.006	-0.006
	(0.025)	(0.032)	(0.040)	(0.021)	(0.079)
Sister × Trading × Low	0.144***	0.149**	0.156**	0.100**	0.160***
	(0.045)	(0.065)	(0.063)	(0.037)	(0.052)
Sister × Trading × High	0.019	0.016	-0.018	-0.029	-0.030
	(0.036)	(0.058)	(0.061)	(0.034)	(0.056)
Observations	5,552	5,452	4,998	5,552	5,474

Notes: Table reports coefficient estimates plotted in Figure 6. We estimate these effects separately by terciles of firms' pre-ETS emission levels. Here, we split our sample by the lower (indicated by Low) and upper tercile (indicated by High) of firms' pre-ETS emission levels. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by a conglomerate of an ETS firm. Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Regressions include firm, industry-year, and province-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Robustness Checks on Confounding Factors

Dep. Var.: ln(Total Emissions)	Announcement (1)	Trading (2)
A. Drop Firms Owned by ETS Firms	0.072**	0.086**
	(0.031)	(0.036)
B. Drop Pilot-Region Firms w/ High Emissions	0.067**	0.083**
	(0.030)	(0.035)
C. Drop Firms in BTH Area	0.065**	0.069*
	(0.030)	(0.034)
D. Control ES10k Firms	0.068**	0.086**
	(0.030)	(0.035)
E. Control ES10k Firms & Related Firms	0.073**	0.095**
	(0.030)	(0.036)
F. Drop ES10k Firms	0.091**	0.143***
	(0.044)	(0.040)
G. Drop ES10k Firms & Related Firms	0.084*	0.184***
	(0.043)	(0.056)
H. Drop Firms w/ Different Product Code	0.085**	0.072**
	(0.034)	(0.035)

Notes: This table shows robustness checks of the main results in Table 2. Column (1) presents coefficient estimates for Sister×Announcement, where Sister is an indicator for ETS-sister firms and Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Column (2) presents coefficient estimates for Sister×Trading, where Trading is an indicator for the trading period (2013–2015) of the ETS pilots. Panel A excludes firms if their parent companies are directly regulated by the ETS. Panel B excludes firms if their emissions are above the threshold of the corresponding pilot region as listed in Table A1. Panel C excludes firms located in the Beijing-Tianjin-Hebei area. Panel D adds a control variable indicating whether the firm itself has been regulated by the "Top 10,000" Energy Savings Program. Panel E adds a control variable indicating whether the firm itself or its sisters have been regulated by the "Top 10,000" Energy Savings Program. Panel F excludes firms regulated by the "Top 10,000" Energy Savings Program. Panel G excludes firms if they or their sisters are regulated by the "Top 10,000" Energy Savings Program. All the regressions control firm, province-year, and industry-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Robustness Checks on Alternative Matching Methods

Dep. Var.: ln(Total Emissions)	Announcement (1)	Trading (2)
A. Alternative Matching Covariates		
Total Emissions, Output	0.067**	0.083**
	(0.030)	(0.035)
Energy, Output	0.094***	0.114**
	(0.030)	(0.049)
Total Emissions, Emission Intensity, Energy	0.060**	0.112*
	(0.025)	(0.060)
B. Alternative Matching Units		
1:2 Matching	0.069**	0.097**
	(0.027)	(0.039)
1:3 Matching	0.075***	0.122***
	(0.026)	(0.036)

Notes: This table shows robustness checks of the main results in Table 2. Column (1) presents coefficient estimates for Sister×Announcement, where Sister is an indicator for ETS-sister firms and Announcement is an indicator for the announcement period (2011–2012) of the ETS pilots. Column (2) presents coefficient estimates for Sister×Trading, where Trading is an indicator for the trading period (2013–2015) of the ETS pilots. In Panel A, we perform the matching based on alternative sets of covariates. In Panel B, we use 1-to-2 or 1-to-3 nearest matching. All the regressions control firm, province-year, and industry-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Robustness Checks on Alternative Measures of Carbon Emissions

VARIABLES	Total Emissions	Emission Intensity	Energy	Energy/ Output	Emission/ Energy
	(1)	(2)	(3)	(4)	(5)
A. Excluding Natural Gas from Carbon Emission Calculation					
Sister × Announcement	0.062*	0.001	0.058	-0.004	0.005
	(0.031)	(0.036)	(0.038)	(0.042)	(0.011)
Sister × Trading	0.090**	0.011	0.088*	0.008	0.002
	(0.037)	(0.039)	(0.043)	(0.047)	(0.012)
Observations	5,552	5,552	5,552	5,552	5,552
B. Excluding Firms with Non-zero Natural Gas Consumption					
Sister × Announcement	0.042	-0.005	0.039	-0.008	0.003
	(0.036)	(0.041)	(0.043)	(0.049)	(0.013)
Sister × Trading	0.081*	-0.005	0.090*	0.003	-0.009
	(0.045)	(0.042)	(0.050)	(0.049)	(0.011)
Observations	4,468	4,468	4,468	4,468	4,468

Notes: This table shows robustness checks of the main results in Table 2. In Panel A, we exclude natural gas consumption from our calculation of carbon emissions. In Panel B, we exclude firms that have positive natural gas consumption from our sample. Regressions include firm, industry-year, and province-year fixed effects. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.