Carbon Leakage within Firm Ownership Networks: Evidence from China's Regional Carbon Market Pilots*

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Abstract

This paper evaluates the carbon leakage of China's regional emission trading scheme (ETS) pilots. By leveraging firms' ownership networks, we examine whether the regionally fragmented ETS pilots lead to emissions and production reallocation from regulated firms to unregulated sibling firms utilizing the matched difference-in-differences (DID) approach. The data pertain to a unique panel of firm tax records and their ownership in the manufacturing and public utility sectors during the 2008-2015 period. Our findings demonstrate unambiguous evidence that China's ETS leads to a 9 percent increase in carbon emissions of non-ETS firms in the same ownership network as sibling ETS firms. The emission leakage occurs during the announcement and trading phases. The mechanism analyses further reveal that the leakage is driven by regulated firms' relocation of production activities, low-emission firms, only under the mass-based rule, and fewer regulatory risk areas. Finally, accounting for the effects of China's ETS pilots on both regulated firms and their siblings, our estimated aggregate effect of carbon regulation on firm emissions is positive and statistically insignificant.

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

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1 Introduction

Concerned with climate change, governments across the globe have implemented market-based instruments, such as carbon taxes and emission trading schemes (ETS), to curb the ever-increasing greenhouse gas emissions. However, these climate policies, covering certain regions (e.g., the California cap-and-trade program) or some industries (e.g., China's regional ETS pilots), are fragmented and localized, creating substantial variations in regulation stringency across jurisdictions. Carbon emissions abated in one jurisdiction could be offset by the emissions leaked in other jurisdictions. Such carbon leakage jeopardizes the global climate integrity and raises pressing concerns about economic competitiveness across nations. Despite extensive literature that has quantified carbon leakage, most studies indirectly proxy the leakage by carbon embodied in trade flow (Aichele and Felbermayr, 2015) or industry-level energy intensity (Cosbey et al., 2019), hence fail to directly and accurately trace out the leakage. Building upon computational general equilibrium model simulations (Carbone and Rivers, 2017) or leveraging asymmetries in energy prices (Sato and Dechezleprêtre, 2015), this strand of literature is silent on providing causal evidence. With most work focusing on a country or sectoral setting, empirical evidence at the firm level receives scant attention.

To fill these research gaps, we seek to identify carbon leakage within firm ownership networks. We exploit China's regional ETS pilots as a quasi-natural experiment. China announced carbon market pilots in seven jurisdictions in 2011 and started carbon trading in 2013. These regional ETS pilots regulate a list of firms from various sectors covering the manufacturing and non-manufacturing industries. The variations of regulation stringency across regions, years, and sectors provide an ideal causal setting to explore firms' strategic behaviors towards carbon compliance. To unravel the mechanism, we explore how leakage occurs and where it shifts. Lastly, we comprehensively assess the aggregate impact of carbon pricing on abated and leaked emissions.

We leverage firms' ownership networks to construct the treatment and control groups.

The ownership networks define a boundary within which the relocation of production activities and carbon emissions from regulated firms are more likely to occur due to knowledge sharing or established relationships (Giroud and Mueller, 2015, 2019; Chen et al., 2021*b*). If an ETS firm could escape carbon compliance by shifting production to its unregulated siblings, one would expect an increase in both output and emissions from ETS-sister firms, defined as non-ETS firms within the same conglomerate of the ETS firm. In comparison, for each conglomerate without any ETS firms, we define these non-ETS firms as unrelated firms akin to Chen et al. (2021*b*). These unrelated firms would have few economic incentives to shift around emissions within the conglomerate, hence serving as potential control groups. Thus, our identification strategy employs a matched difference-in-differences (DID) design that compares outcomes of interest between ETS-sister firms and unrelated firms during the pre- and post-ETS periods. To mitigate the potential selection bias, we use a one-to-one matching procedure based on pre-ETS characteristics to find a set of similar unrelated firms as control groups.

Our empirical analysis takes advantage of a unique panel dataset of firm tax records during 2008 – 2015 collected by the Chinese State Administration of Tax (i.e., the counterpart of the Internal Revenue Service in China). This database has a broad coverage of firms across sectors. It records comprehensive information on their geographical characteristics and economic activities. More importantly, the dataset reports detailed firm-level energy consumption by source, including coal, oil, natural gas, and electricity. The rich set of variables allows us to explore the effect of carbon trading on emission leakage. It further facilitates uncovering the underlying channels through which firms respond.

We find a significant rise in carbon emissions from ETS-sister firms (i.e., nonETS firms within the same conglomerate of ETS ones) after the announcement of China's ETS pilots. The effect is pronounced during the allowance trading phase. The results survive a series of robustness checks that address confounding factors or alternative matching methods. Our findings are economically meaningful. Cui et al. (2021) show a 16.7% reduction in carbon emissions from regulated firms. In comparison, we find that the ETS-sister firms increase carbon emissions by 8.3%, indicating that regulated firms have managed to escape a large portion of emissions. A simple conversion indicates the carbon leakage rate (i.e., units of emissions leaked per unit of emissions abated) is around 44.9%, [1] which is on par with the estimate simulated by Fowlie and Reguant (2022).[2]

We examine the effects on firm economic activities and energy consumption to explore the underlying mechanisms. ETS-sister firms significantly increase energy consumption, outputs, sales, and labor inputs. In contrast, there is no impact on their emission intensity, energy mix, energy efficiency, or productivity. Our results overwhelmingly suggest that ETS firms shift their production and emissions to unregulated parties to escape carbon regulations. Besides, we observe the substantial heterogeneity along the dimension of firm-level characteristics. The leakage, accompanied by the reallocation of production resources, is mainly driven by small-emission ETS-sister firms that are free from carbon pricing risks. Such leakage effect is muted among large ETS-sister firms as their emissions may hit the threshold of being included in ETS pilots.

Moreover, we observe the pivotal role of the ETS stringency in facilitating carbon leakage. ETS pilots with higher carbon prices, larger turnover rates of carbon allowances, and the mass-based allowance allocation rule put strong pressure on regulated firms to shift around carbon emissions. Such leaked emissions will move toward ETS-sister firms that reside in non-regulatory risk areas, including non-ETS pilots and less air-polluted regions. Finally, accounting for the overall effects of China's ETS pilots on regulated firms and their unregulated siblings indicates that the aggregate impact of carbon pricing on firm emissions is positive but statistically insignificant.

This paper adds to a growing literature that has adopted computational general equi-

[1] The mean of carbon emissions appeared in Cui et al. (2021) is $63,576 = \exp(11.06)$ metric tons. In comparison, the mean of carbon emissions in this study is $19,148 = \exp(9.86)$ metric tons. On average, one ETS regulated firm have 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 $44.9\% = 3 \times (19,148 \times 8.3\%)/(63,576 \times 16.7\%)$.

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

librium models to quantify the impacts of incomplete carbon pricing on 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). Depending on the postulated model structures and parameters, these studies have simulated carbon leakage, ranging from negative to positive rates. A handful of empirical works have sought to estimate whether carbon pricing causes leakage through trade channels (Aichele and Felbermayr, 2015; Aldy and Pizer, 2015; Naegele and Zaklan, 2019). Using incomplete carbon pricing across regions, we focus on leakage within a country. We aim to provide firm-level causal evidence in identifying carbon leakage.

This paper contributes to a burgeoning empirical literature that has made successful attempts on evaluating the carbon mitigation impacts of carbon pricing, such as cap-and-trade program in California (Fowlie, 2010; Fowlie, Holland and Mansur, 2012), the EU ETS (Martin et al., 2014; Jaraite and Di Maria, 2016; Borenstein et al., 2019; Bayer and Aklin, 2020; Colmer et al., 2020), and China's regional ETS pilots (Cao et al., 2021; Cui et al., 2021).[3] Our paper is the first empirical study that identifies the firm-level carbon leakage arising from China's regional ETS pilots. Leveraging comprehensive ownership networks, we contribute to the literature by unraveling a within-conglomerate leakage channel through which a conglomerate could respond to ETS by shifting carbon emissions from regulated to unregulated areas within its business networks. Our results extend the understanding of the effectiveness of market-based climate instruments. Building upon the eight-year experiences of regional carbon ETS pilots, China's national ETS market, with the power sector only included in its initial stage, has started to operate in late 2021 and will further expand to carbon-intensive manufacturing sectors shortly. Our findings call for an urgent

[3]The growing literature has explored the effects of carbon pricing on 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), labor employment (Curtis, 2017), management practice (Yong et al., 2021), and other economic adjustments (Commins et al., 2011; Martin, Muûls and Wagner, 2016; Marin, Marino and Pellegrin, 2018).

need to redesign the carbon pricing tools by regulating conglomerates that have the flexibility to reallocate emissions among subsidiaries.

This paper contributes to another strand of literature seeking to identify the spillover effects of local economic shocks on firm economic adjustments through firm ownership networks (Hanna, 2010; Giroud and Mueller, 2015; Seetharam, 2018; Giroud and Mueller, 2019; Cui and Moschini, 2020),[4] and more importantly, to quantify emission leakage (Gibson, 2019; Samy Soliman, 2019; Chen et al., 2021*b*; Sadayuki and Arimura, 2021; Bartram, Hou and Kim, 2022; Dechezleprêtre et al., 2022). Leveraging the variations of local environmental regulations (i.e., the CAAA in the United States), Gibson (2019) investigates the cross-media pollution leakage within firms, while Samy Soliman (2019) further explores the extensive (plant relocation) and the intensive margin (air emissions of volatile organic compounds). Chen et al. (2021*b*,*a*) focus on an energy-saving program in China. Utilizing the comprehensive conglomerate ownership network, they estimate emission leakage from regulated plants to unregulated plants within the same conglomerate. A handful of recent work seeks to detect within-firm carbon leakage but with mixed evidence. Using the Japanese regional ETS, Sadayuki and Arimura (2021) find the negative carbon leakage within firms. For the EU ETS, Dechezleprêtre et al. (2022) 's findings indicate no evidence of leakage among the multinational firms. Bartram, Hou and Kim (2022) investigate the California cap-and-trade program. Their findings point to a pivotal role of financial constraints in emission leakage in which financially constrained firms shift emissions and output from regulated plants in California to similar unregulated plants in other states. Our paper explores the spillover of incomplete carbon pricing with highlights on the mechanisms of how leakage occurs and where it goes. Moreover, we have attempted to

[4]Utilizing local environmental policy shocks featured by county-level nonattainment status under the Clean Air Act Amendments (CAAA) in the United States, Hanna (2010) explores the FDI decisions of multinational companies, while Cui and Moschini (2020) examine the closure decision of multi-plant firms. Giroud and Mueller (2015) exploit exogenous local shocks to investment opportunities spill over to other plants, whereas Giroud and Mueller (2019) study local negative employment shocks by exploiting the regional variations in house prices during the Great Recession. Seetharam (2018) investigates the spillover effects of a hurricane, an exogenous natural disaster, from disrupted to undisrupted plants within multi-plant firms.

estimate the general equilibrium effects of the ETS on both regulated and unregulated firms. Our paper also emphasizes the difference in policy outcomes between the partial and general equilibrium framework, calling for caution when evaluating the effectiveness of climate policies.

The remainder of this paper is organized as followers. Section 2 introduces a brief background of China's regional ETS pilots and their distinct features. Section 3 provides empirical strategy addressing the identification challenges. Section 4 presents data sources, variables construction, and descriptive statistics. Section 5 shows empirical results, mechanism, heterogeneity, robustness checks, and the general equilibrium effects of ETS. Section 6 concludes.

2 China's ETS Background

China's earliest experience of carbon ETS started with a voluntary carbon offset scheme in the early 2000s through the Clean Development Mechanism created by the Kyoto Protocol (Karplus, Zhang and Zhao, 2021). In late 2011, the National Development and Reform Committee (NDRC) formally approved seven regional carbon market pilots, including four municipalities (i.e., Beijing, Shanghai, Tianjin, and Chongqing), one special economy zone (i.e., Shenzhen), and two provinces (i.e., Guangdong and Hubei). These pilots were then launched in 2013 and started trading carbon allowances henceforth. The NDRC sets forth general guidelines and oversees the planning and development of each ETS pilot. Following general guidelines, each pilot is granted the flexibility to design its own market rules, including sector coverage, allowance allocation, and others (Zhang, Wang and Du, 2017). In the Online Appendix, Table A1 summarizes the ETS policy designs across pilots.

China's regional carbon market pilots have three distinct features critical to the identification strategy. First, seven pilots exhibit a wide range of heterogeneity in sector coverage, allowing us to pin down unregulated firms akin to the regulated ones across regions. These pilots cover major emitters in various sectors, ranging from manufacturing to non-manufacturing industries, with the different thresholds determined by annual emissions or energy consumption. The sectoral and spatial variations enable us to compare emissions outcomes between regulated ETS firms with similar unregulated ones within-firm ownership networks.

Second, the pilot ETS exhibits substantial variation in policy stringency across regions. It provides an economic incentive of spatially reallocating production resources within-firm networks, leading to carbon leakage. Total emission allowances and their allocation rules vary across pilots.[5] Despite sharing similar protocols, each pilot has established its measurement, reporting, and verification (MRV) system. Noncompliances are often subject to various financial and non-financial penalties. On top of that, China's regional ETS adopted two main allowance allocation rules: mass-based and rate-based. The former sets a cap on total emissions, and the latter regulates emission intensity (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Goulder et al., 2022).[6] The rate-based rule is regarded as an implicit subsidy to firm production since additional output value increases the number of allowances that regulated firms receive (Fischer, 2001; Fischer and Newell, 2008). Such flexibility creates less incentives for emission abatement among regulated firms (Goulder and Morgenstern, 2018; Pizer and Zhang, 2018; Cui et al., 2021; Goulder et al., 2022). The fragmented regional pilots and localized policy designs create substantial variations in the stringency of carbon pricing across regions and sectors. In response, a regulated firm has incentives of reallocating production resources, henceforth

[5]Guangdong issues the most carbon allowances (388 Metric tons [Mt]), while Shenzhen has the least (30 Mt). The covered shares of emissions in each pilot range from 33 percent for Hubei to 60 percent for Tianjin. While almost all pilots allocate allowances for free, carbon allowances can only be traded within the same pilot. Guangdong and Shenzhen auction a small share of allowances – up to 3 percent.

[6]Under the mass-based rule, regulators set a total number of allowances in advance of each compliance period. If a regulated entity's emission level exceeds the allocated allowances, it must purchase additional allowances from the carbon market for compliance. In most cases, the allowance allocation is exogenous to a facility's production level during the compliance period. Under the rate-based system, regulators set an emission intensity target rather than an emission cap for regulated firms. The number of allowances depends on a firm's output and historical emission rate and might be adjusted at the end of each compliance period according to a firm's production level.

emissions, to unregulated siblings within-firm networks. Given that a rate-based yields less regulatory pressure than the mass-based, emission leakage may occur for regulated firms under the latter rather than the former.

Third, the pilot ETS experienced two phases: announcement (2011 to 2012) and trading (since 2013). Although little is known about the coverage and stringency of ETS pilots during the announcement phase, firms in pilot regions may have some expectations of carbon ETS risks due to their historical carbon emissions. During the trading phase, detailed allowance rules yield explicit carbon prices and allowance liquidity. Thus, carbon leakage is likely to differ between the announcement and trading phases. We further differentiate these leakage effects between these two phases.

3 Empirical Strategy

3.1 Identification Challenge

Our identification strategy is subject to three challenges in identifying the causal impact of ETS on firm-level emission leakage. First, how to define a boundary of emission leakage poses a daunting threat to the definition of treatment. One firm is related to many others through the ownership network. It can relocate production activities with a relatively lower cost to other sibling firms due to knowledge sharing or established relationships (Giroud and Mueller, 2015, 2019; Chen et al., 2021*b*). To escape emission abatement pressures, ETS firms may opt-out and shift production and emissions toward related siblings. Such an ownership network forms a boundary where emission leakage would likely occur.

Figure 1 illustrates firm ownership networks. Each power plant icon indicates an emitting firm regulated under the ETS or free from carbon pressures. ETS firms are in black, while non-ETS firms are in gray. The black arrow indicates that a firm owns or invests in other firms, forming the ownership network. The treatment of interest in this paper does not set on ETS firms but on ETS-sister firms (marked in shaded blue), which are not regulated by the ETS but are part of a conglomerate including at least one ETS firm. Circled by dashed gray lines, unrelated firms are defined as those within a conglomerate that includes none of the ETS firms. We conjecture that carbon pricing may be mirrored with changes in carbon emissions and production activities in ETS-sister firms but not for those unrelated firms. Comparing emission outcomes between these two groups could shed light on the potential leakage arising from ETS.

[Insert Figure 1 about here]

The second threat arises from the construction of reasonable counterfactuals for treated firms. ETS-sister and unrelated firms could differ significantly in their pre-treatment characteristics, leading to a selection-biased treatment effect. Figure 2 shows the statistical differences in means between treated and control firms along the dimension of firm-level attributes, including carbon emission, energy consumption, output, sales, and investment. The left panel plots the results for the unmatched sample. In all three years before the ETS (i.e., 2008, 2009, and 2010), one could notice sharp differences in the emission outcomes and key economic characteristics between the treated and control firms. Thus, a simple and naive DID model would not yield an unbiased estimate of China's ETS effects on emission leakage.

[Insert Figure 2 about here]

To address this issue, we employ a one-to-one nearest neighbor matching technique. We first pin down unrelated firms as those non-ETS firms and not in the ownership networks of any ETS ones. For each ETS-sister firm, we then match the closest unrelated firm within the same sector and similar historical firm-level attributes in terms of the shortest Mahalanobis distance. This distance is calculated based on total emissions and emission intensity three years before the announcement of ETS pilots (i.e., 2008, 2009, and

2010).[7] Besides, matching within the sector-year cell could help control the sector-specific time-variant unobservable factors that affect both treated and control units. We allow the matching with replacement to avoid introducing extra bias in selecting control units, ensuring that each treated has the closest control unit. For robustness checks, we employ alternative matching estimators and different sets of covariates for the Mahalanobis matching procedure.

The third pressing challenge is the potential confounding energy and environmental policies that affect firms' emission abatement or reallocation activities. Two notable policies coexist. First, regional-level environmental policy coexists. In 2011 the Ministry of Ecology and Environment targeted Beijing, Tianjin, and Hebei (BTH), one of the most polluted regions in China, to dramatically heighten air pollution regulation to clean up regional air pollution (e.g., $PM_{2.5}$). Since carbon dioxide is co-emitted with many air pollutants in most cases, this regional air pollution coordination and control is plausible to affect firms' incentives for carbon mitigation. To address this, we drop the firms from the BTH region in the robustness check. Second, firm-specific exposure to energy policy presents a major challenge. One notable energy policy, the Top 10,000 Energy Saving program (henceforth, the ES10k program) initiated by NDRC in late 2011, aimed at reducing the energy use of Chinese industrial firms (Filippini et al., 2020; Chen et al., 2021*a*). This program covers the top 10,000 energy users in the manufacturing sector, accounting for about 60% of nationwide energy consumption in China. This policy can affect emissions of both directly regulated firms and unregulated but related firms. To address this concern, we rerun the regression by including an indicator for the ES10K program or excluding firms potentially affected by this policy. Other industrial or regional overlapping policies

[7]The distance-based matching performs well in searching the control units with the closest values of characteristics to match with the treated ones. However, the performance would be impaired due to relatively many covariates (more than 8) (Rubin, 1979; Zhao, 2004; Stuart, 2010). In our exercise, a large number of selected covariates tend to result in fewer matched pairs since there are many missing and dropped values in some key economic indicators. Thus, we choose the covariates that are strongly correlated with the outcomes to ensure the close similarity between treated and control units while still bringing the highest number of matched pairs.

that might affect firm emissions, such as the *Action Plan on Air Pollution Prevention and Control* ("Air Ten") announced in 2013 (Karplus, Zhang and Zhao, 2021), could be easily captured by a flexible control of fixed effects at the industry-year and province-year levels.

3.2 Baseline Model

Using China's ETS pilots as a quasi-natural experiment, we leverage firms' ownership networks to construct the treatment and control groups. If an ETS firm strategically escapes the compliance pressure by shifting production activities, one would expect an increase in output and emissions from ETS-sister firms. In comparison, for each conglomerate without any ETS firms, we would expect the muted effects of carbon pricing on changes in emissions from unrelated firms. Therefore, our identification of emission leakage compares ETS-sister firms (i.e., the treatment group) to unrelated firms (i.e., control firms) during the pre-and post-ETS periods. This empirical strategy is related in spirit to recent work exploiting the variation in environmental regulation among multi-plant firms for causal inference (Gibson, 2019; Samy Soliman, 2019).

We carefully assess the credibility of the matching procedure using balancing tests. Specifically, we compare the sample means of covariates between the treatment and matched control groups. In Figure 2, we find no significant differences between the two groups in all covariates used and even those not used in the matching approach. These results suggest that our matching strategy performs well in extracting reasonable unregulated firms, similar to the regulated firms within the same sector before the announcement of ETS.

With the control group constructed by the matching approach, we further employ a DID approach to identify emission spillovers induced by China's ETS pilots. For firm i in sector j from province r in year t, we estimate the following equation:

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

In this form, the outcome variable, Y_{ijrt}, denotes firm carbon emissions (total emissions and emission intensity, in logarithms) or economic performance (output, input, and productivity). The dummy Sister_i is an indicator for ETS-sister firms, equalling one if firm i is unregulated but is a sibling of regulated firms, and zero otherwise. The dummy Announcement_{it} equals one if the region where firm i's regulated sister is located has announced its participation in ETS at time t. The dummy Trading_{it} takes a value of one if firm i's regulated sister has entered the trading phase at time t.

To account for unobservable determinants for carbon emissions, we include firm fixed effect γ_i that controls for unobservable time-invariant firm attributes. We also add industry-year fixed effect δ_{jt} and province-year fixed effect η_{rt} to capture industry- and region-specific time-varying unobservables. At last, ε_{ijrt}, is an idiosyncratic error.

The parameters of central interest, β_1 and β_2, capture the spillover effects of China's ETS pilots on firm emissions in the announcement and the trading phases, respectively. With the matched sample, we can consistently estimate the parameters using ordinary least squares. The standard errors are clustered at the industry level to allow for within-industry correlations.

4 Data

4.1 Data Sources

The primary data pertain to a panel of manufacturing firms reported by the Chinese National Tax Survey Database (CNTSD), a large-scale annual survey launched in 2007 and conducted by the Ministry of Finance of China and the State Administration of Taxation of China. This survey includes firms from a wide range of industries and regions across the country. It provides detailed information on ownership, location, sector, and economic activities. Unlike another widely used Chinese firm-level dataset (i.e., the Annual Survey of Industrial Firms) that only reports large firms, the CNTSD covers a large number of small and young firms as well as large firms (Liu and Mao, 2019).

One notable feature of this dataset is the detailed information on firm-level energy consumption by energy type. The energy inputs are composed of coal, oil, natural gas, and electricity. This allows us to calculate firm-level carbon emissions in conjunction with standardized carbon emission conversion factors provided by China's Department of Energy Statistics. Moreover, the detailed quantity information on the type of energy used also helps us to capture any reallocation from higher-carbon to lower-carbon energy inputs that may result from China's ETS pilots. We also collect detailed firm-level production and balance-sheet information (output, sale, investment, value-added, labor employment, capital, material input purchases, etc.).

Another key data source is China's Administrative Registration Database (CARD), collected by the State Administration of Industry and Commerce. This database reports the registration information of all firms in China, including shareholders and subsidiaries. This unique data feature helps us construct a firm ownership network. Moreover, it allows us to identify and trace out ETS-sister firms.

The ETS rules in the seven regional pilots are compiled from the official websites of local Development and Reform Commissions, which regulate carbon emissions and carbon markets, summarized in Table A1 in Appendix. We compile a list of regulated firms and classify them into a rate- or mass-based system according to the allowance allocation rules reported in Table A2 in Appendix. In addition, we obtain the carbon allowance trading data – including price and volume – from the seven carbon exchanges.

4.2 Variable Construction

Our primary dependent variables of interest are emissions and emission intensity. We consider both direct emissions from the combustion of fossil fuels and indirect emissions from purchased electricity. Emissions are calculated from the CNTSD energy consumption data by source and by carbon emission factors.[8] Emission intensity is defined as total carbon emissions per value of gross outputs. Moreover, we also consider energy consumption, metric tons of standard coal equivalents,[9] and energy intensity, energy consumption per value of gross outputs.

Firm economic attributes include output value, value-added, sales, labor, capital, wage, investment, and export. This rich set of firm attributes allows us to decompose the efficiency by capital intensity (capital per labor), labor efficiency (output per labor), and capital efficiency (output per capital). Firm-level productivity is proxied by total factor productivity (TFP) using two standard approaches in the economics literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003).

The market performance of seven regional carbon markets is proxied by two indicators: carbon price and turnover rates. The former, the logarithm carbon prices, captures the effects of carbon pricing. The latter, the ratio of trading volume to the total allowances issued, represents the activeness of market participation in trading allowances. For those non-ETS regions, carbon price and turnover rates are coded as zeros.

4.3 Summary Statistics

We adopt a meticulous and rigorous data cleaning and merging process proposed by Cui et al. (2021).[10] This process includes the removal of observations with missing, zero values or drastic changes in key variables across years. Finally, the cleaned dataset includes 413 regulated firms and 40,219 unregulated firms. The final dataset after matching has in total of 5,555 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.

[8] In Appendix, Table A3 reports detailed emission factors for each energy type.

[9] 1 ton of coal equivalent = 29307 gigajoules (GJ).

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

[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 resources. Moreover, we examine the heterogeneous spillover effects of ETS along the dimension of firm characteristics, policy features, regional carbon market performance, and city air pollution exposure. Furthermore, we conduct a series of robustness checks regarding potential confounding environmental and energy factors and alternative model specifications. Lastly, we seek to estimate the general equilibrium effect of the ETS on firm emissions.

5.1 Spillover Effects on Firm Emissions

We estimate the baseline model in Equation (1) with different combinations of fixed effects to capture unobservable firm-specific characteristics and time trends. Table 2 presents the coefficient estimates and standard errors. We differentiate the spillover effects into two phases: announcement (2011–2012) and trading (2013–2015). The preferred model specification, listed in Column (3), controls for the firm, province-year, and industry-year fixed effects.

[Insert Table 2 about here]

We document consistently positive coefficients for total emissions in both the announcement and trading phase, suggesting that the ETS leads to a statistically significant increase in total emissions from ETS-sister firms, i.e., those nonETS firms but owned by the same conglomerate of ETS firms. According to our preferred model estimate, ETS-sister firms' total emissions increased by 6.7% in the announcement phase. It provides evidence that ETS firms had started shifting their emissions after the announcement of ETS pilots. The effect becomes larger when trading starts, and there are explicit carbon prices. On average, we find an 8.3% increase in ETS-sister firms' total emissions during the trading phase. The magnitude is economically meaningful. In comparison, Cui et al. (2021) document a 16% decrease in total emissions from ETS firms. Combining these results, we can infer that ETS firms reallocate a large portion of emissions to their unregulated sisters.

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 that the parallel trend holds before the treatment, we estimate the dynamics of firm emissions using the event-study framework. Specifically, we include leads and lags of the ETS-announcement dummy in the baseline regression to trace out the year-by-year effects:

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

In the above equation, ETS_t, is an indicator for the announcement year of ETS pilots (i.e., 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 effects as a test for the 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 one year before the announcement.

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, which supports the parallel trends assumption.

[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 mechanism, we examine the spillover effects of ETS pilots on a series of energy-related and economic characteristics in both level and intensity measures. Figure 4 plots the coefficient estimates and their corresponding 95% confidence intervals.

[Insert Figure 4 about here]

Consistent with the baseline results, the ETS slightly increases ETS-sister firms' energy consumption in the trading phase. Among firms' economic attributes, we find significant increases in ETS-sister firms' outputs, sales, and value-added in both the announcement and trading phases. It provides evidence that energy consumption and production activities from ETS-regulated firms have been shifted to their unregulated sisters. Our findings are consistent with Cui et al. (2021) that document a significant decrease in ETS firms' labor and capital. These results overwhelmingly imply that ETS firms shift their production activities and corresponding emissions to unregulated sisters to mitigate the emission abatement pressures.

Regarding the intensity measures, we find muted impacts on ETS-sister firms' energy intensity and emission per energy, suggesting that ETS-sister firms do not engage in energy conservation or efficiency improvements. Along this line, the ETS has no statistically significant effects on their capital-labor ratio and total factor productivity (TFP).[11] These findings together suggest no improvements in energy efficiency or TFP for the ETS-sister firms but the reallocation of production activities.

[11]TFP is estimated following Olley and Pakes (1996).

5.3 Heterogeneity

5.3.1 Firm Characteristics

We explore the heterogeneous responses of emission leakage along the dimension of firms' historical attributes before the ETS. These attributes include the level (i.e., emission, energy, age, and output) and intensity (i.e., emission intensity, energy intensity, and TFP) measures used in the above mechanism investigation. For each firm characteristic, we take three-year observations before the launching phase (i.e., the 2008 - 2010 period). Using pre-ETS values could mitigate concerns that our sample classification might be potentially affected by the treatment itself. We then split the sample into two groups based on whether a firm's attribute lies above or below the median in the three-year window. The high group is defined as those firms' attributes above the median, while the low group is defined as those below the median. For each firm-level attribute, we estimate the baseline leakage effects by splitting samples into low and high groups. Figure 5 plots coefficient estimates and their corresponding 95% confidence intervals. The top panel shows the estimates for the announcement effect, while the bottom panel shows the estimates for the trading effect.

[Insert Figure 5 about here]

In the announcement phase, the low group of ETS-sister firms respond differently than the high group if the group classification is set on levels (i.e., emission, energy, age, and output). Specifically, small ETS-sister firms, those with lower emissions, less energy consumption, younger, and smaller outputs, tend to emit more than their counterparts in response to the ETS treatment. If the group classification is at intensity indexes, such as emission intensity, energy intensity, and TFP, we don't observe substantial differences in carbon emissions between the two groups of the ETS-sister firms. In the trading phase, we document similar findings but with a bit larger magnitude of leakage estimates. Combining these findings indicates that emission leakage is likely to occur among those small firms. One key determinant of enrolling in local ETS pilots lies in the size of carbon emissions or related energy consumption. On the one hand, large ETS-sister firms have a potentially large capacity to absorb the reallocated production resources, henceforth emitting more carbon. On the other hand, they may trigger the carbon mitigation pressure as the total emissions rise above the threshold. In sharp contrast, small ETS-sister firms have less carbon pricing pressure. Their leakages are unlikely to be caught.

The carbon leakage is likely to occur among those small ETS-sister firms. Along this line, we further examine whether their production activities are shifting along with the leakage. We focus on ETS-sister firms with fewer historical carbon emissions before the ETS. The sample is split into two groups based on whether a firm's emission lies above or below the median three years before the treatment (i.e., 2008, 2009, and 2010). Figure 6 plots coefficient estimates and their corresponding 95% confidence intervals. The top panel shows the estimates for the announcement effect, while the bottom panel shows the estimates for the trading effect.

[Insert Figure 6 about here]

We observe a clear pattern in the heterogeneous adjustment of production activities between the two groups of ETS-sister firms in response to the ETS. 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 substantially 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 fairly silent on shifting around production activities and leakage. These findings further provide corroborating evidence supporting the conjecture that carbon leakage occurs among small ETS-sister firms.

5.3.2 Policy Feature

The regional ETS mainly adopts two types of allowance allocation rules: mass-based and rate-based allocations. The former regulates total emissions, while the latter governs the intensity. The rate-based allocation provides an implicit subsidy for production, and firms face less pressure of emission abatement (Goulder and Morgenstern, 2018; Cui et al., 2021). To examine the heterogeneity in emission spillovers under different allocation rules, we estimate the baseline model separately for firms whose sisters are regulated by the mass-based rule and for firms whose sisters are regulated by the rate-based rule. Table 3 reports the estimation results. In columns (1) and (2), we find that the increase in ETS-sister firms' total emissions only occurs if ETS firms are subject to the mass-based allocation rule. This result further demonstrates that ETS firms mainly escape regulation pressures by shifting production-related emissions to their unregulated parties, which cannot affect emission intensities. Therefore, we do not find any evidence of emission spillovers if firms are regulated by the rate-based allocation rule.

[Insert Table 3 about here]

State-owned enterprises (SOE) may respond differently to the ETS than non-SOE. We further explore the role of firm ownership in the leakage effect by splitting the sample. Column (3) reports the effects on SOE, while Column (4) shows the results for non-SOE. In both the announcement and trading phases, we document negative coefficients for SOE but positive coefficients for non-SOE. All coefficients are statistically significant. These findings indicate that the emission leakage is mainly documented by non-SOE firms but not for SOE ones.

Where does the leakage go? We further split the sample by ETS regions or not. Columns (5) and (6) show the results. We find no significant impacts on carbon emissions of ETS-sister firms located in ETS pilot regions. Although these firms are not directly subject to carbon pricing, the potential reallocation of production and emissions may trigger the mitigation pressure if the emission hits the ETS threshold. Standing in sharp contrast, we document a positive and statistically significant effect on other regions during the trading phase. For those ETS-sister firms located in other regions that are free from ETS pressures, they have fewer regulatory risks and could take more emissions shifted away from their regulated siblings.

5.3.3 Carbon Price and Allowance Liquidity

The heterogeneity in policy design across ETS pilots results in differential carbon prices and allowance liquidity. During our sample period, the daily carbon price of the regional pilots ranges from \$1.38/tCO_2e to \$20.88/tCO_2e, with the average at \$5.6/tCO_2e. The average turnover rate, defined by the ratio of exchanged allowances to total allowances, is 0.018. The low carbon price and infrequent allowance trading reflect an inactive carbon market (Zhang, Wang and Du, 2017).

We add an interaction term between the sister-trading dummy with either carbon price or turnover rate in the baseline model to investigate the heterogeneous effects. The estimation results are presented in Table 4. Column (1) suggests that a 1% increase in carbon price leads to a 2.2% increase in ETS-sister firms' total emissions. Similarly, as indicated by Column (2), one percentage point increase in the turnover rate can raise ETS-sister firms' total emissions by 2%. ETS pilots with a higher carbon price or turnover rate put more pressure on regulated firms, and therefore these firms are expected to have stronger incentives to shift emissions.

[Insert Table 4 about here]

5.3.4 City Air Pollution Exposure

Would carbon leakage shift away to air-polluted areas? We retrieve city-level average $PM_{2.5}$ and SO_2 concentrations and their corresponding exposure over the pre-ETS period (i.e., 2007-2010). We then split the sample by the median of these air quality indexes. The dummy Low indicates air pollutant concentrations or exposure below the median, while the dummy High says the opposite. Based on the baseline equation, we add interaction terms between the sister-ETS dummy with these two air quality proxies. Table 5 shows the results. Columns vary by alternative pollutants and air quality measures. The estimated coefficients for the Low dummy interaction terms are consistently positive and statistically significant for both the announcement and trading phases. These findings suggest that carbon leakage shifts toward ETS-sister firms located in less air-polluted cities. One plausible interpretation is to avoid any regulatory risks. Air pollutants are often co-emitters of carbon emissions. Less air-polluted areas might implement less stringent environmental regulations than more air-polluted areas. Shifting carbon emissions from ETS pilots to less air-polluted areas may help avoid the compliance pressures charged by other air quality regulations.

[Insert Table 5 about here]

5.4 Robustness Checks

To test the stability of the baseline conclusions, we run a rich set of robustness checks regarding confounding factors, alternative matching covariates, alternative matching units, and alternative emission measures.

[Insert Figure 7 about here]

Confounding Factors. One concern is that subsidiaries of ETS firms are also covered by the ETS. In that case, some ETS-sister firms can be directly regulated if their parent company is an ETS firm. To address this concern, we re-estimate the baseline model by excluding firms whose parent companies are regulated by the ETS. Another concern centers around the regional-level or industry-level regulations, which are common shocks to different firms and, therefore, will be absorbed by the province-year and industry-year fixed effects. Besides, firm-level environmental or energy policies may confound our identification of the spillover effects. During our sample period, the Chinese government implemented stringent air pollution control policies targeting Beijing, Tianjin, and Hebei (BTH) areas, which overlapped with the ETS pilot regions. To test the robustness of our results, we drop firms located in the BTH area and re-estimate our model. One pressing challenge is the Top 10,000 Energy Saving (ES10k) program that requires energy-intensive manufacturing firms to meet energy-saving targets. To mitigate this concern, we use two measures to capture the ES10k effect: (i) the indicator for whether a firm itself has been regulated by the ES10k; and (ii) the indicator for whether a firm itself or its sisters has been regulated by the ES10k. We also exclude the firms if they or their sisters are regulated by the ES10k and re-run the baseline model.

Alternative Matching Covariates. In the baseline model, we perform the Mahalanobis distance-based matching based on two covariates, i.e., total emissions and emission intensity, which are two key determinants for a firm's regulatory status in a pilot region. To check the robustness of our main results, we consider alternative sets of covariates, including (i) total emissions and output; (ii) energy consumption and output; (iii) total emissions, emission intensity, and energy consumption.

Alternative Matching Units. One may worry about the 1-to-1 nearest neighbor matching leading to the small sample size. To increase it, we also consider another two alternative matching algorithms: 1-to-2 and 1-to-3 nearest neighbor matching, both based on the same covariates used in the baseline model (i.e., total emissions and emission intensity).

Alternative Emission Measures. One data caveat is zero or missing observations in natural gas consumption. To address this concern, we either exclude the natural gas from emission calculation or drop firms with non-zero natural gas consumption.

Product Similarity. ETS-regulated firms and their unregulated sisters may have different business scopes, leading to an unclear mechanism of production reallocation between them. To resolve this issue, we gather product codes for ETS firms and their sisters. The production of similar products under the same category is more likely to be substitutable among firms. In our sample, more than 80% unregulated sister firms share the same product category as their ETS-regulated firms. We further exclude the unregulated sister firms whose products are not in the same category as those produced by their ETS-regulated siblings.[12]

Overall, our baseline conclusions survived all these robustness checks.

5.5 Aggregate Effect of ETS Pilots

So far, we have provided unambiguous evidence that ETS pilots affect unregulated firms that are sisters to those regulated ones. To investigate the aggregate effect of ETS pilots on firm emissions, we estimate a variant of the baseline model that accounts for the effect on both regulated firms and their unregulated sisters. Specifically, we consider all ETS firms and their sisters as the treatment group. Then, we construct the control group using the same matching procedure as before. We estimate the baseline model with the matched sample, replacing the sister dummy with the ETS group dummy that equals one for ETS firms and their sisters.

Table 6 shows the estimation results. We find that the aggregate effect of ETS pilots on firm emissions is positive and statistically significant during the announcement period. Column (1) suggests that, on average, there is a 6.6% increase in total emissions among ETS firms and their sisters. We also find a slight increase in energy consumption and output. The coefficients for total emissions, energy consumption, and output are still positive but become insignificant during the trading period. We do not find any significant effect on intensity measures. These results suggest that the unintended emission spillovers substantially attenuate the effectiveness of ETS pilots in reducing carbon emissions. Carbon regulation under the ETS pilots only causes a redistribution of carbon emissions across firms but does not affect total nationwide emissions.

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

[Insert Table 6 about here]

6 Conclusion

The world expects carbon ETS to play a pivotal role in meeting the 1.5°C global warming target. Whether this climate policy could achieve a carbon mitigation target or induce carbon leakage lies in the central stage of policy debate. Utilizing the variations of policy stringency created by China's regional ETS pilots across sectors, regions, and years, this paper leverages comprehensive firms' ownership networks to identify the emission leakage impacts of ETS and their economic adjustments. Our findings suggest unambiguous evidence that carbon pricing leads to remarkable emission leakage. ETS firms shift emissions to sibling non-ETS firms within the same ownership network. Despite a 16 percent reduction in carbon emissions of ETS firms relative to unregulated ones (Cui et al., 2021), our findings further indicate a 9 percent increase in carbon emissions of non-ETS firms that are siblings of ETS ones. The mechanism unravels that carbon leakage is accompanied by the relocation of production resources within the firm ownership network, particularly for those under the mass-based allocation rule.

This paper sheds light on carbon ETS expected to achieve mitigation targets and carbon neutrality committed by many countries. Our results show that conglomerate responds to carbon pricing by adjusting production resources and carbon emissions within the ownership network. Increasing awareness of such carbon leakage makes the design and assessment of carbon pricing tools more challenging. An optimal carbon policy should account for the potential leakage channel through which regulated firms may escape compliance. It also calls for a comprehensive assessment of ETS effects in a general equilibrium setting.

Another profound policy implication centers around the nationwide China ETS operated in July 2021. China has been reassured to adopt the rate-based TPS approach in the national ETS, covering the electricity sector in the initial stage. Our findings show that the mass-based allowance allocation creates a stronger incentive for emission leakage than the rate-based rule, echoing concerns on the implicitly subsidizing role of the rate-based TPS (Pizer and Zhang, 2018; Goulder and Morgenstern, 2018; Goulder et al., 2022). Our analysis calls for an urgent need for policy intervention in designing the national ETS that will cover a wide range of manufacturing sectors in the second stage.

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Figures and Tables

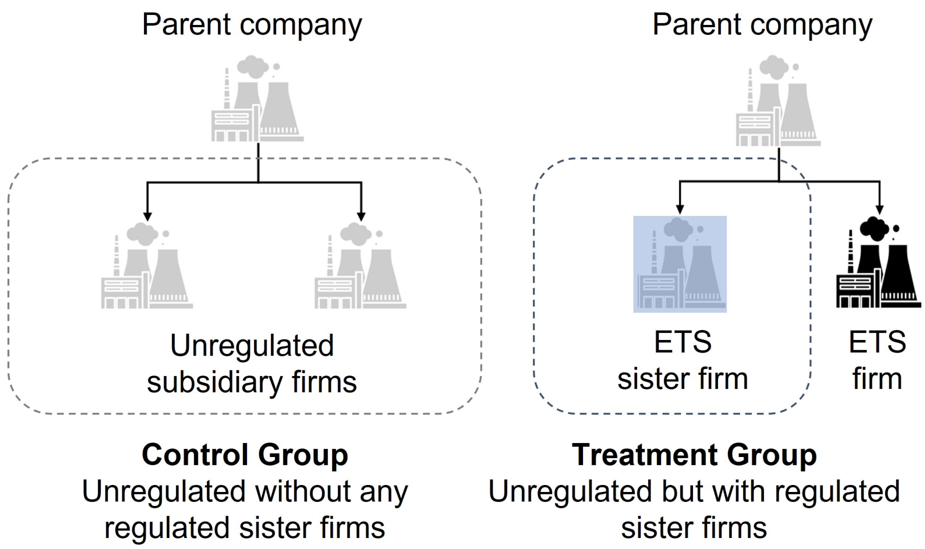

Figure 1: Definition of The Treatment and Control Groups

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-regulated 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 parent company of an ETS-regulated firm. The circled ones are un-related firms, i.e., firms whose ownership network does not have any ETS-regulated entities.

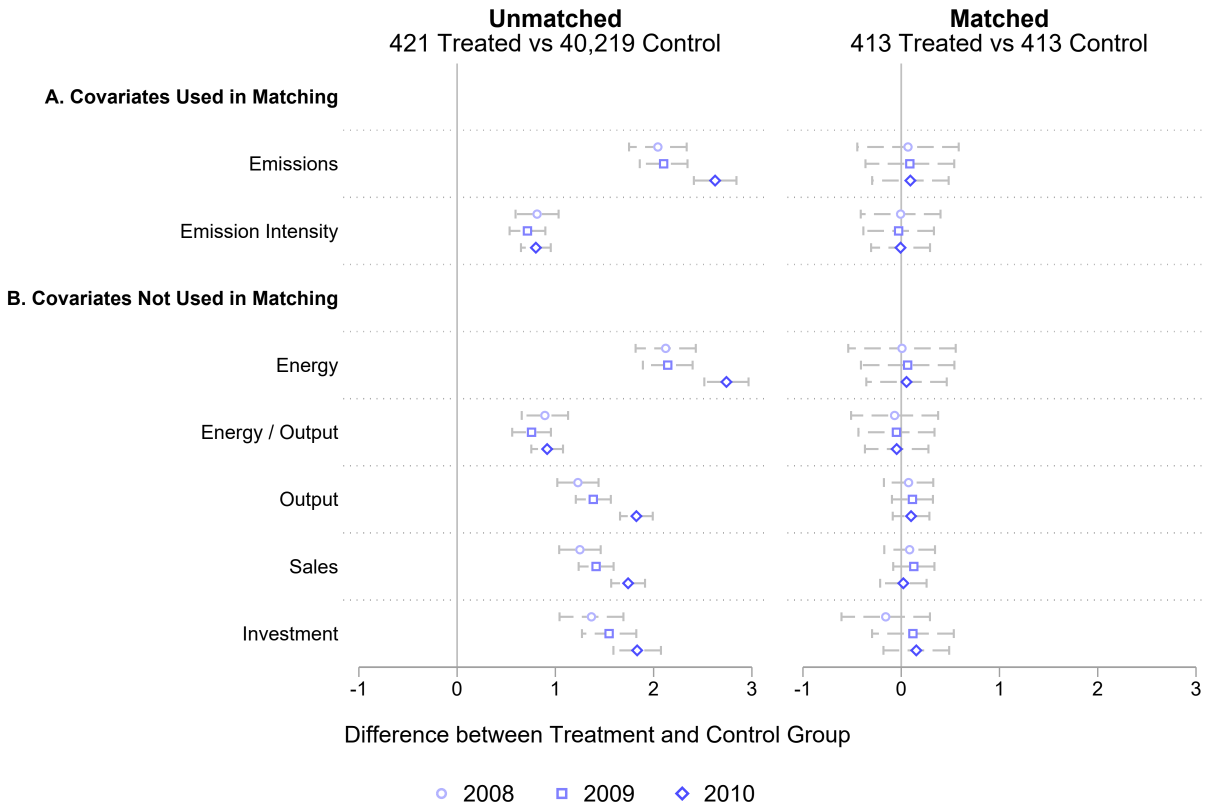

Figure 2: Balancing Test

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

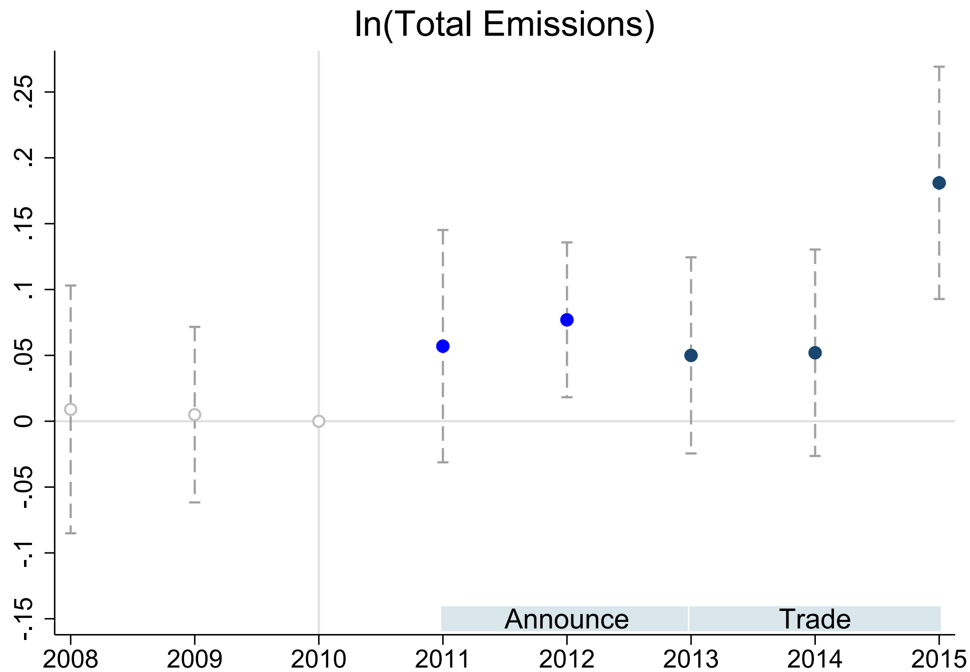

Figure 3: Event Study Estimates of the Spillover Effect

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.

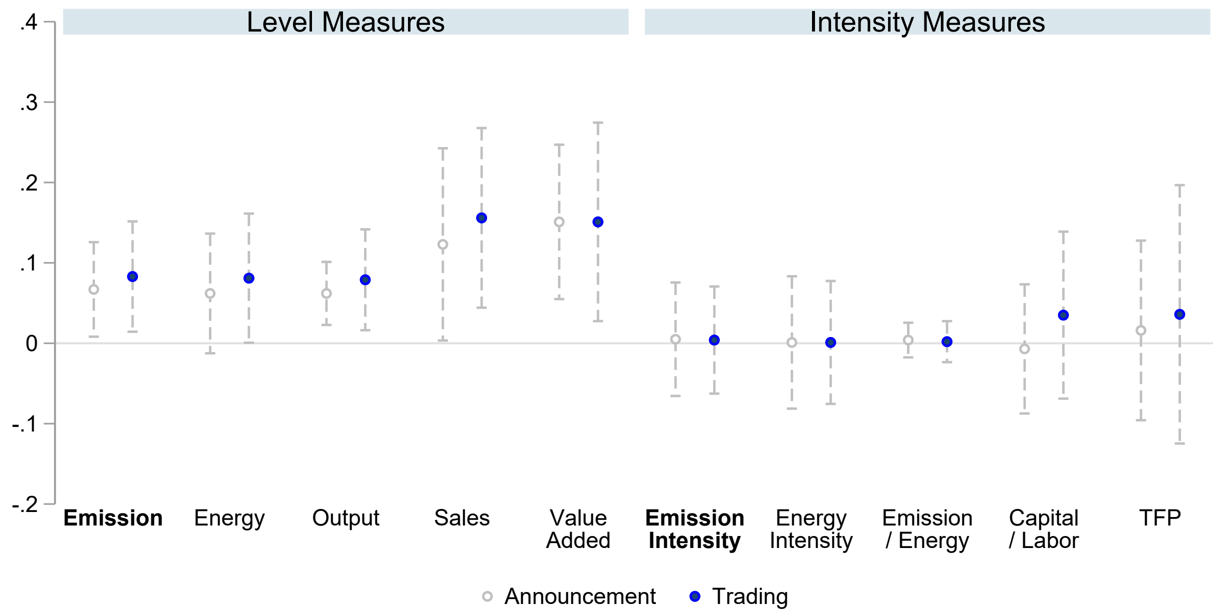

Figure 4: Effects on ETS-Sister Firms' Level and Intensity Measures

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 A6.

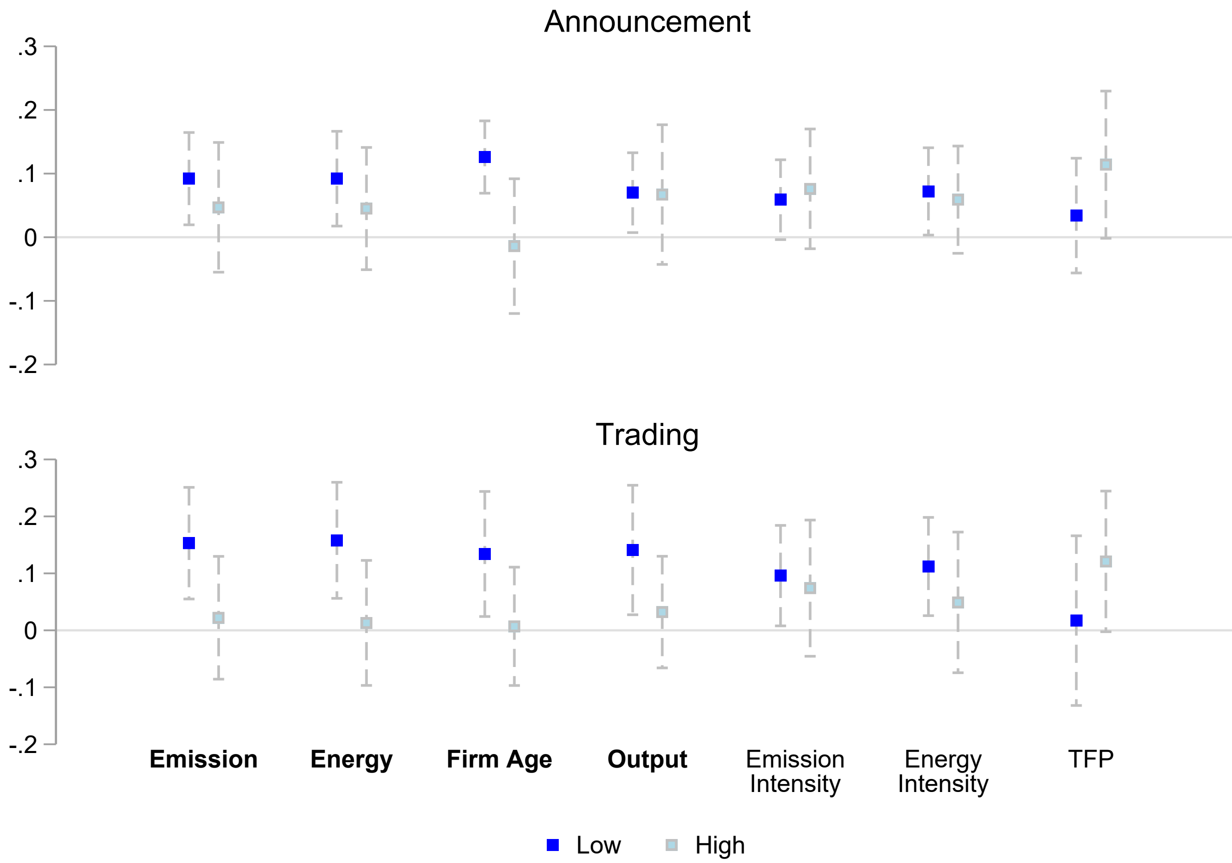

Figure 5: Heterogeneous Effects on Emissions by Firm Characteristics

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 A7.

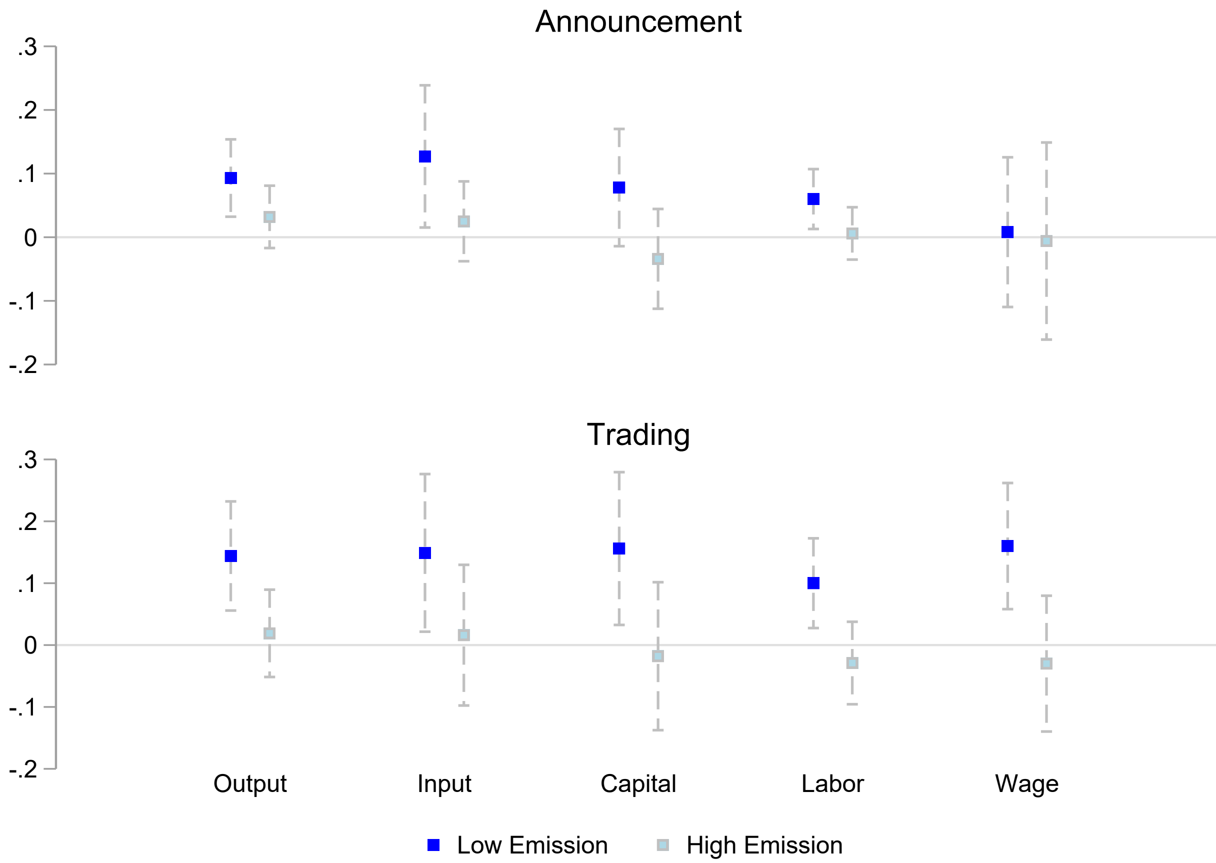

Figure 6: Heterogeneous Effects on Production Activities by Pre-ETS Emission Levels

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 A8.

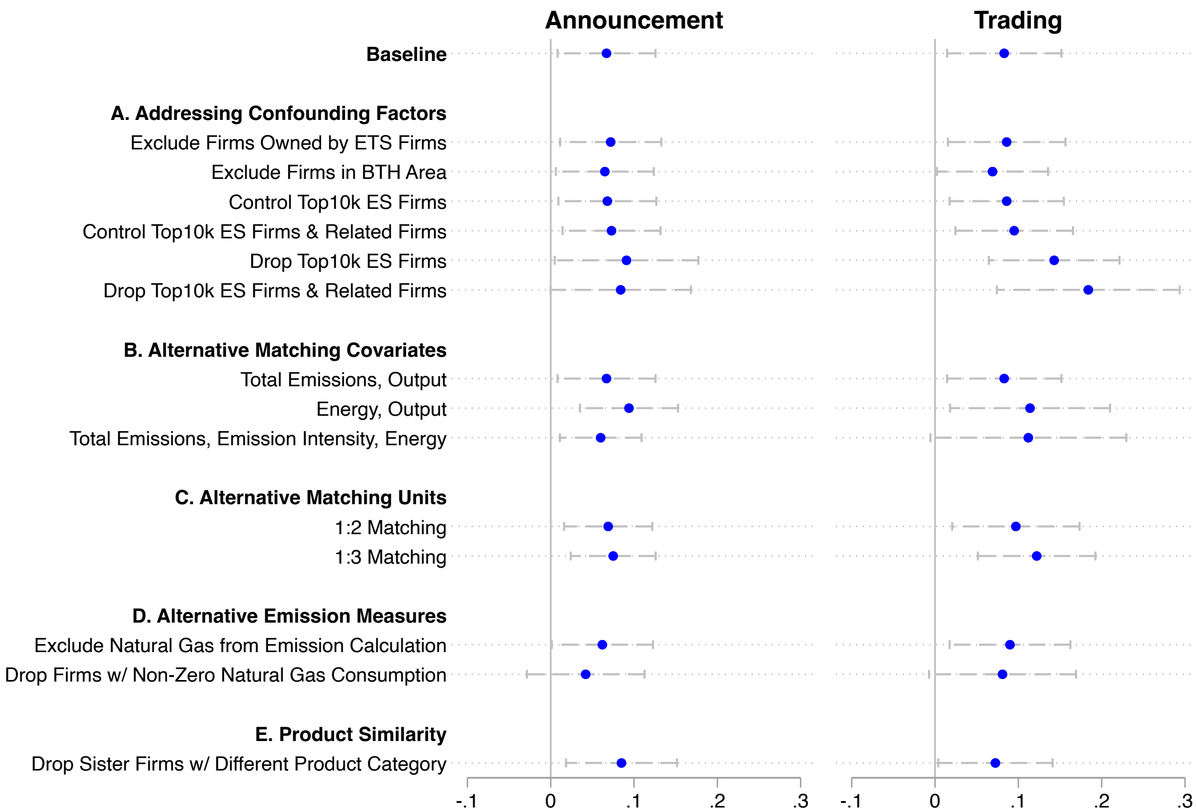

Figure 7: Robustness Checks

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 addresses confounding factors by (i) excluding firms if their parent companies are directly regulated by the ETS; (ii) excluding firms located in the Beijing-Tianjin-Hebei area; (iii) adding a control variable indicating whether the firm itself has been regulated by the "Top 10,000" Energy Savings Program; (iv) adding a control variable indicating whether the firm itself or its sisters have been regulated by the "Top 10,000" Energy Savings Program; (v) excluding firms regulated by the "Top 10,000" Energy Savings Program; (vi) excluding firms if they or their sisters are regulated by the "Top 10,000" Energy Savings Program. In Panel B, we perform the matching based on alternative sets of covariates. In Panel C, we use 1-to-2 or 1-to-3 nearest matching. In Panel D, 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 E, we drop unregulated sister firms whose products are not in the same category of 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 – 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 the parent company of an ETS-regulated 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:	Allocation Rule		Ownership		Firm Location	
	Mass Based	Rate Based	SOE	Non-SOE	ETS Pilots	Other Regions
ln(Total Emissions)	(1)	(2)	(3)	(4)	(5)	(6)
Sister × Announcement	0.080**	0.016	-0.625***	0.081**	0.024	0.083**
	(0.037)	(0.039)	(0.022)	(0.034)	(0.060)	(0.036)
Sister × Trading	0.105**	0.037	-0.650***	0.085**	0.076	0.079
	(0.049)	(0.060)	(0.008)	(0.038)	(0.106)	(0.054)
Firm FE	✓	✓	✓	✓	✓	✓
Province-Year FE	✓	✓	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓	✓	✓
Observations	2,624	2,858	276	4,843	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 based on firms whose sisters are regulated by the ETS under the mass-based vs the rate-based allocation rule. Columns (3) and (4) present estimates for state-owned firms (SOE) and non-state-owned firms (Non-SOE). 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-regulated 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: Effects of Carbon Price and Allowance Liquidity

Dep. Var.	ln(Total Emissions)	
	(1)	(2)
Sister × Announcement	0.065*	0.044
	(0.033)	(0.035)
Sister × Trading × Price	0.022**	
	(0.010)	
Sister × Trading × Turnover		2.021*
		(1.120)
Firm FE	✓	✓
Province-Year FE	✓	✓
Industry-Year FE	✓	✓
Observations	5,524	5,524

Notes: Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by the parent company of an ETS-regulated 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. Carbon price and turnover rate are only available for ETS-sister firms during the trading period (2013–2015) and equal zero otherwise. Standard errors in parentheses are clustered at the industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: 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: 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 city population. Sister is an indicator for ETS-sister firms, i.e., unregulated firms owned by the parent company of an ETS-regulated 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 6: 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 regulated 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A Online Appendix

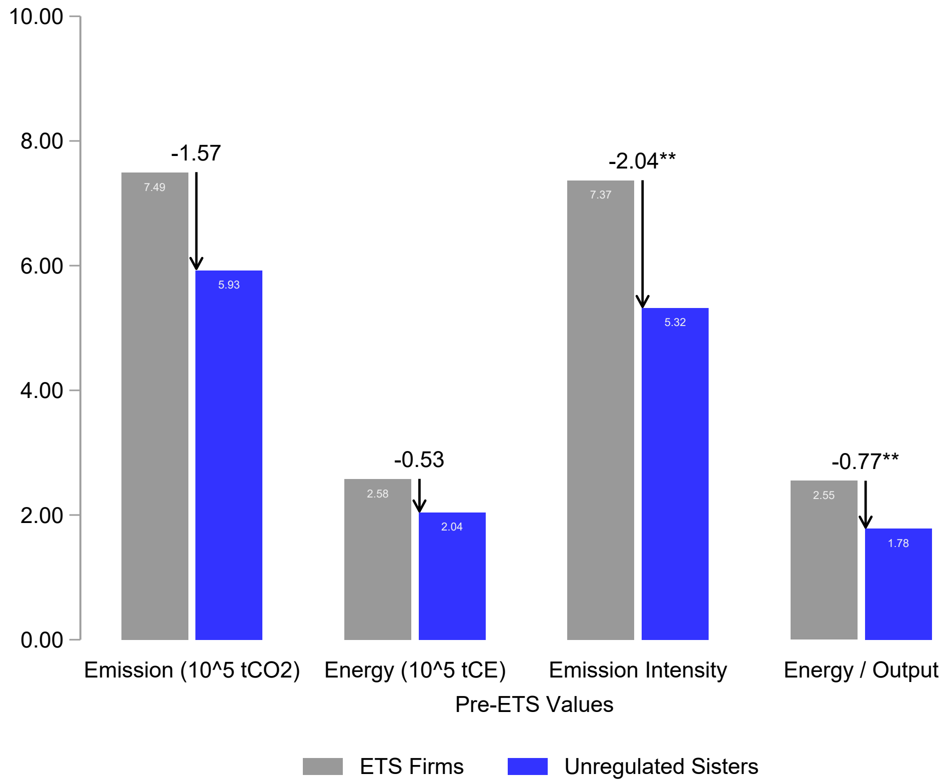

Figure A1: Emission Profiles of ETS Regulated Firms v.s. Their Unregulated Sisters

Notes: The figure plots mean values and their corresponding 95% confidence intervals of emission profiles of ETS regulated firms (in gray) and their unregulated sisters (in blue) before the announcement of China's ETS pilots. The values are adjusted by controlling for year fixed effects.

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[7]
	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 process), 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 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	Control	P-value	Treated	Control	P-value
		(1)	(2)	(3)	(4)	(5)	(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 ($k = -3$)	0.009
	(0.048)
Sister × ETS ($k = -2$)	0.005
	(0.034)
Sister × ETS ($k = 0$)	0.057
	(0.045)
Sister × ETS ($k = 1$)	0.077**
	(0.030)
Sister × ETS ($k = 2$)	0.050
	(0.038)
Sister × ETS ($k = 3$)	0.052
	(0.040)
Sister × ETS ($k = 4$)	0.181***
	(0.045)
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 the parent company of an ETS-regulated 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: 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 the parent company of an ETS-regulated 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 A7: 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 firm's total emission measured in logarithm. 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 the parent company of an ETS-regulated 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 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 the parent company of an ETS-regulated 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: 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 Firms in BTH Area	0.065**	0.069*
	(0.030)	(0.034)
C. Control ES10k Firms	0.068**	0.086**
	(0.030)	(0.035)
D. Control ES10k Firms & Related Firms	0.073**	0.095**
	(0.030)	(0.036)
E. Drop ES10k Firms	0.091**	0.143***
	(0.044)	(0.040)
F. Drop ES10k Firms & Related Firms	0.084*	0.184***
	(0.043)	(0.056)

Notes: This table shows robustness checks of the main results in Table 2. Columns (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. Columns (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 located in the Beijing-Tianjin-Hebei area. Panel C adds a control variable indicating whether the firm itself has been regulated by the "Top 10,000" Energy Savings Program. Panel D adds a control variable indicating whether the firm itself or its sisters have been regulated by the "Top 10,000" Energy Savings Program. Panel E excludes firms regulated by the "Top 10,000" Energy Savings Program. Panel F excludes firms if they themselves 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 A10: 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). Columns (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. Columns (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 A11: 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). Columns (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. Columns (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 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.