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NRE Discussion Papers No. 2025-04

May 2025

Division of Natural Resource Economics, Graduate School of Agriculture, Kyoto University

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May 15, 2025

Discussion Papers

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Offshoring Pollution? The Impact of China's Pilot Emission Trade Scheme on
Offsite Investment

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Abstract

This study investigates whether market-based environmental regulations affect the locations of subsidiary firms. Our analysis uses China's pilot carbon emission trade scheme (ETS) implemented by the Chinese government in 2013, in which carbon markets were established in ETS regions but not in others. Using firm-level panel data and a triple difference estimation across provinces, industries, and years, we address the critical limitations of previous studies that use the difference-in-differences method. We compare targeted industries in ETS regions with three control groups to accurately estimate the causal effect of the ETS by controlling for industry-specific trends and concurrent regional policies, among which the latter has not been appropriately addressed. We find that implementing the pilot ETS significantly enhances offsite establishment, thus supporting the pollution haven hypothesis. Moreover, the carbon market plays an important role, with firms increasing their subsidiaries in non-ETS regions with increasing carbon prices.

Keywords: pollution haven hypothesis, emission trade scheme, carbon price, triple difference method

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1. Introduction

As global climate change becomes increasingly severe, carbon emission trading has emerged as a key market-based mechanism for reducing greenhouse gas emissions. Endowed with abundant natural resources and immense energy consumption, China faces considerable challenges for sustainable development. Since 2008, China has topped the annual list as the largest emitter of carbon dioxide (CO₂), representing nearly 29% of the global emissions in 2022 (Crippa et al., 2023). To reduce emissions and combat climate change, China launched its regional Carbon Emissions Trading Scheme (ETS) in 2013. It selected seven cities or provinces (Beijing, Shanghai, Tianjin, Shenzhen, Chongqing, Guangdong, and Hubei) as the pilots, where a cap-and-trade system was established to incentivize emissions reduction (National Development and Reform Commission, 2011). Under this market-based mechanism, firms that want to increase their emissions beyond a set cap must purchase permits from others willing to sell them (Jaffe et al., 2009).

A substantial body of research demonstrates the effectiveness of carbon pricing in reducing emissions (Fowlie et al., 2012; Haites, 2018; Rafaty et al., 2025), promoting energy efficiency (Martin et al., 2014; Peeters et al., 2016), and stimulating innovation in low-carbon technologies (Calel & Dechezleprêtre, 2016, Compernelle et al., 2022). In the context of China's pilot ETS, studies have found positive effects at the macro and micro levels. Macro-level analyses highlight the role of the ETS in economic growth (Zeng et al., 2024) and emissions reduction (Xuan et al., 2020; Zhang et al., 2020; Wang et al., 2024), whereas micro-level research shows how the ETS influences corporate investment (Zhang & Wang, 2021), productivity (Xiao et al., 2021), and environmental performance (Yao et al., 2023).

However, the effectiveness of market-based environmental mechanisms may be compromised by unintended consequences, as stated by the pollution haven hypothesis (PHH). The PHH argues that firms may seek to avoid the cost of stringent environmental regulations and high energy prices by relocating production to countries with lax environmental regulations (Levinson & Taylor, 2008). China's pilot ETS experience is suitable to test this hypothesis rigorously because most prior PHH

evidence comes from international trade studies, in which many confounding factors, such as trade barriers and cross-country institutional differences, might have affected the results (Copeland & Taylor, 1994; Levinson & Taylor, 2008; Kellenberg, 2009; Cherniwchan, 2017). As a domestic case without such unnecessary confounding factors, recent evidence from China's pilot ETS suggests that some firms may follow the PHH. Studies have found that regulated firms are increasingly establishing subsidiaries in non-ETS regions of China, presumably to avoid compliance costs (Qi et al., 2023; Shen et al., 2024; Pan & Yu, 2024). Although these studies provide suggestive evidence, the econometric approaches are limited in establishing reliable causal effects.

This study aims to advance the literature by testing the PHH in the context of China's pilot ETS using an improved empirical approach and novel variables. This study makes five key contributions to the literature. First, we address two critical limitations of the existing studies that use the difference-in-differences (DID) method. Some studies might have underestimated the policy effects by failing to account for industry-specific heterogeneous effects (Qi et al., 2023; Pan & Yu, 2024). This underestimation could be attributed to the inclusion of non-targeted industries from the ETS regions in the treatment group. Another group of DID analyses restricted their sample to ex-ante defined pollution-intensive industries (Shen et al., 2024). This approach might confuse the direct effect of the ETS with the indirect effect of other policies in the same region that are implemented simultaneously and applied to all industries. For example, the Air Pollution Prevention and Control Action Plan, launched in 2013 to reduce several types of air pollution in the pilot ETS regions (Beijing, Tianjin, Shanghai, and Guangdong), might have accelerated the pollution haven behavior. This effect must be eliminated to accurately estimate the impact of the pilot ETS. We fill this gap by employing a triple difference (DDD) methodology that controls for both industry- and region-specific factors and, thus, better identifies the causal effect of the pilot ETS on firm behavior.

Second, the study focuses on the evaluation of carbon markets. While most studies overlook how carbon-pricing mechanisms shape firm responses, our study explicitly examines price effects in the analytical context of DDD. This builds on Wu's (2022)

pioneering work on price effects on emissions reduction at the county level; however, we extend the analysis to firm-level investment responses. Third, several studies have not paid sufficient attention to the satisfaction of the stable unit treatment value assumption (SUTVA) which is a precondition for applying DID or DDD. Under the SUTVA, the untreated groups should not be affected by the treatment. However, studies using county-level CO₂ emissions as the dependent variable potentially suffer from spatial spillover effects, in which emission reductions in regulated areas may be (partially) transferred to nonregulated areas through PHH behavior (Wu, 2022; Yang et al., 2024). This violates the SUTVA, resulting in an underestimation of the positive impact through a negative spillover effect. Our focus on the outcome variable is the number of subsidiary firms established by the parent firm. As the ETS affects only the parent firms in the treated regions and their decisions on establishing subsidiary firms, our estimation satisfies the SUTVA. Fourth, existing studies' measures of firms' investment decisions focus primarily on subsidiary counts without considering investment scale or quality (Qi et al., 2023; Shen et al., 2024; Pan & Yu, 2024). We introduce new capital flow measures by examining the number and scale of subsidiaries to capture the presence and depth of offsite investment. Finally, the literature has paid insufficient attention to how firms' existing environmental capabilities affect their responses to the ETS. We fill this gap by conducting a series of heterogeneity analyses that account for firms' green production capabilities, factor intensity, technological sophistication, and geographic location.

We use firm-level panel data from the China Stock Market and Accounting Research Database (CSMAR). The dataset spans the years 2007–2020 and includes detailed information about firms' subsidiary activities, capturing the number of newly established subsidiaries and the amount of registered capital invested in these subsidiaries. Besides our key outcome variables, the CSMAR data provide a set of firm-level characteristics that allow us to control for potential confounding factors and investigate the heterogeneity in firms' responses to the ETS.

Our analysis provides robust empirical support for the PHH within China's pilot ETS framework, indicating that previous studies' findings are confirmed even with the

DDD analyses (Qi et al., 2023; Pan & Yu, 2024; Shen et al., 2024). We also find that, while firms increased in number in non-ETS regions, they reduced the average scale of new subsidiaries. In addition, carbon price plays an important role, with higher carbon prices increasing offsite subsidiaries.

The remainder of this article is organized as follows. Section 2 reviews China's pilot ETS framework. Sections 3 and 4 describe the data and methodology, respectively. Section 5 presents the empirical results and robustness checks. Finally, Section 6 discusses the policy implications and concludes the study.

2. Background

To fulfil China's carbon emission reduction targets by 2020 using a cost-efficient market mechanism, expedite the transformation of economic growth patterns, and upgrade the industrial structure, at the end of 2011, China's State Council issued the Work Plan for Greenhouse Gas Emissions Control during the 12th Five-Year Plan Period. This aimed to "explore and establish a national unified carbon emissions trading market." In response to the State Council's plan, the National Development and Reform Commission, in October 2011, initiated a carbon emissions trading pilot program in seven regions, including the five municipalities of Beijing, Tianjin, Shanghai, Chongqing, and Shenzhen, and two provinces of Hubei and Guangdong.

The pilot ETS adopts a selective regulatory framework for the sectors accounting for 60%–80% of regional emissions, such as electricity, petrochemicals, cement, and steel, while exempting smaller firms under the "managing the big, liberating the small" principle (Center for Energy and Environmental Policy Research, 2023). Two methods are introduced to allocate the emission allowance. The "historical intensity decline method" is applied to industries with incomplete emissions data. This method uses past emissions data to project future allowances. The "industry benchmark method" is used for sectors with accurate emissions data. Quotas are set based on production and efficiency levels (Qi et al., 2018). Furthermore, the ETS pilots implement dynamic adjustments, in which companies that exceed certain emission levels are added to the scheme, whereas those that fall below the thresholds are removed. This ongoing

adjustment motivates companies to reduce their emissions (Zhang et al., 2019).

As of December 31, 2022, the seven pilot carbon markets had completed approximately 34.73 million tons of online quota transactions in 2022, with a transaction volume of RMB 2.02 billion (International Carbon Action Partnership, 2024). Table 1 presents the total online quota transaction volumes, prices, and values. Figure 1 shows the trend of the annual average carbon price and volume for each pilot carbon market since its opening, revealing notable regional differences in trading patterns and price levels. Beijing's market maintained consistently high carbon prices, starting at approximately 50 yuan/ton in 2013 and rising steadily to over 80 yuan/ton by 2019, with a modest cumulative trading volume of 16.4 million tons. By contrast, Guangdong emerged as the most active market, with a cumulative trading volume of 176.02 million tons at substantially lower prices averaging 20.56 yuan/ton. This is because Guangdong's market exhibited a notable decline in prices from approximately 60 yuan/ton in 2013 to approximately 25 yuan/ton in later years while experiencing substantial growth in trading activity.

Hubei demonstrated an intermediate pattern with a substantial trading volume (76.37 million tons) and moderate price levels averaging 22.99 yuan/ton. Hubei's market maintained relatively stable prices between 20–30 yuan/ton throughout this period, with active trading at high volumes. Conversely, the Chongqing market showed limited development, recording the lowest trading volume (9.71 million tons) and relatively low prices averaging 18.28 yuan/ton, with declining price trends and intermittent trading activity.

Figure 1 illustrates the temporal evolution of these markets and reveals the important dynamics of market maturity. While Beijing and Shanghai developed relatively stable price trajectories, the others experienced significant volatility or declining trends. This heterogeneity, combined with the prohibition of interregional trading, suggests persistent market fragmentation.

Recent evidence indicates that even moderate carbon price changes can generate measurable firm responses. A carbon price of 50 yuan/ton increases production costs by 1.8%–3.2% in energy-intensive sectors, which is comparable with the average profit

margins in these industries (Cui et al., 2021). These cost increases create incentives for technological adaptation and strategic responses, including potential production relocation to unregulated regions (Copeland & Taylor, 2004). While the environmental economics literature emphasizes the efficiency of market-based regulation, China's experience complicates this narrative.

3. Data

3.1. Data source

We use data from the CSMAR database, which covers all A-share listed companies on the Shanghai and Shenzhen stock exchanges in China¹. The CSMAR database provides detailed information on subsidiaries, including their geographic locations, ownership structures, and financial data. To ensure data quality, we exclude firms with missing financial information or ambiguous subsidiary details, resulting in a 12.1% reduction in the original sample size. The resulting sample comprised 15,009 observations, spanning the period from 2007 to 2020.

3.2. Variable construction

3.2.1. Independent variable

The key independent variable in this study is a triple interaction term, denoted as *ddd*, which captures the combined effect of a firm's location in an ETS pilot region (*Pilot*), the timing of policy implementation (*After*), and the firm's industry classification (*Industry*). *Pilot* takes a value of 1 for firms located in China's seven ETS pilot regions and 0 otherwise. *After* takes a value of 1 after the year of ETS implementation (2013) and 0 otherwise. *Industry* takes a value of 1 for firms belonging to the eight targeted sectors covered under China's ETS pilots, which include electricity generation, petroleum processing, chemical manufacturing, building materials, steel production, nonferrous metals, papermaking, and air transportation. These sectors are consistent with the national ETS framework implemented in 2022, ensuring a uniform industry classification throughout the sample period. Although Hubei and Chongqing

¹ A-shares are the shares of incorporated companies based in mainland China that are listed on the Shanghai or Shenzhen stock exchanges. These shares are issued in China under Chinese law and are quoted in RMB.

initiated their carbon markets in 2014, we consider 2013 as the treatment year for all pilot regions because firms may have taken preparatory actions following Shenzhen's carbon market launch in June 2013.

3.2.2. Dependent variables

Our study employs two complementary measures to capture firms' production relocation responses: the number of offsite subsidiaries and the subsidiaries' average registered capital. We acquire the data through several steps. First, we obtain the subsidiary catalog from the CSMAR database, which includes geographic information and registered capital for each subsidiary. Second, to isolate production relocation to non-pilot regions, we exclude subsidiaries located in the ETS pilot regions and foreign countries. We then calculate the total number of offsite subsidiaries for each listed firm. This measure is commonly used to capture firm relocation (Qi et al., 2023; Shen et al., 2024; Pan & Yu, 2024).

Besides the subsidiary counts, we introduce the average registered capital of offsite subsidiaries as another dependent variable. This measure reflects the scale and intensity of a firm's relocation investments. By calculating the offsite subsidiaries' total registered capital and dividing it by the subsidiary count, we obtain the average registered capital per subsidiary. This variable provides insights into the depth of investment and the parent firm's long-term commitment to regulatory compliance. The distinction between these two measures is crucial as larger subsidiaries with higher registered capital may exhibit different responses to the ETS than smaller subsidiaries. While the subsidiary count indicates the presence of relocation, the average registered capital captures investment depth. Incorporating both variables allows a more comprehensive analysis of firms' relocation strategies in response to the ETS policy.

3.2.3. Control variables

To account for the factors that may influence firms' pollution transfer decisions, we include three groups of control variables: firm characteristics, financial indicators, and institutional factors.

Firm characteristics: *The number of employees* captures the parent firms' operational capacity. *Firm age* is included as an indicator of accumulated experience

and established production patterns, potentially affecting the costs of adapting to new regulations (Coad et al., 2016).

Financial indicators: The *asset–liability ratio* is used as a proxy for the financing constraints that might influence firms’ ability to invest in cleaner technology or relocate production (Shao & Chen, 2022). The *fixed assets* control for asset specificity and potential relocation costs because firms with higher fixed asset intensities may face greater barriers to production transfers.

Institutional factors: *State-owned enterprises (SOE)* in China are subject to stricter government oversight than private firms when participating in carbon trading schemes. To account for this, we include a dummy variable that equals 1 for SOEs and 0 for non-SOEs (Voinea et al., 2022).

3.2.4. Additional measures

To examine the impact of carbon trading policies on firms’ relocation decisions, we incorporate two additional variables: *carbon price* and *green factory*.

Carbon price: The *carbon price* variable captures the market dynamics of the ETS pilots. As carbon prices fluctuate across pilot regions and over time, this variable allows us to investigate how firms’ responses to the ETS policy vary based on actual price levels. We calculate the annual average carbon prices from daily transaction data for each pilot ETS platform.

Green factory: The *green factory* variable accounts for firms’ existing environmental capabilities, which may influence their ability to adapt to the ETS policy. We measure a firm’s green factor based on whether it or any of its subsidiaries have been certified as green factories by the Ministry of Industry and Information Technology of China. This certification is awarded to firms that meet stringent standards for land-use efficiency, clean production, waste recycling, and low-carbon energy consumption. We obtain green factory data from the Ministry’s website and match them with our sample of listed companies. The green factory variable takes a value of 1 if a firm or any of its subsidiaries have obtained the green factory certification and 0 otherwise. By incorporating this variable, we assess whether firms with stronger environmental performance are better positioned to respond to the ETS policy without

resorting to production relocation. Table 2 presents the descriptive statistics for all the variables used in our analysis, providing an overview of the key features of our dataset.

4. Methodology

4.1. Identification strategy

This study employs a triple difference (DDD) approach to identify the causal effect of China's ETS pilots on firm offshoring behavior. Identifying this effect requires controlling for any systematic factors of offsite investment in the treatment group that are correlated with, but not due to, the pilot ETS. Specifically, the first difference comes from the comparison between ETS and non-ETS regions; the second difference compares the targeted industries covered under the ETS and non-targeted industries; and the last difference is due to the ETS implementation in 2013, which divides the sample into pre- and post-treatment periods.

Figure 2 shows how these three dimensions of variation create our distinct treatment and control groups. Our primary treatment group (Group A) consists of ETS-targeted industries operating in the pilot regions. The DDD estimator compares the changes in offshoring activity for this group against three sets of control groups: non-targeted industries in pilot regions (Group B), targeted industries in non-pilot regions (Group C), and non-targeted industries in non-pilot regions (Group D).

Recent studies examining China's ETS pilots have primarily employed a DID approach (Qi et al., 2023; Shen et al., 2024; Pan & Yu, 2024). Although these analyses capture the average policy effects, they may underestimate the true impact by failing to account for industry-specific trends. Our DDD approach allows us to control for a full set of province-industry, province-year, and industry-year fixed effects, in which all potential omitted variables varying at the province (time-varying and time-invariant) and industry (time-varying and time-invariant) levels have been appropriately dealt with (Gruber, 1994; Cai et al., 2016).

Our empirical analysis faces a challenge arising from Shenzhen, a sub-provincial municipality within the Guangdong province, which simultaneously implemented its own carbon market with Guangdong's provincial system in 2013. This administrative

structure creates potential complications in the province-level DDD framework. While standard econometric practices might suggest treating Shenzhen as an independent unit, the absence of comparable sub-provincial regions in our control groups makes this approach methodologically unsound. Instead, we aggregate data from Shenzhen with Guangdong, which may have introduced some imprecision in our estimates. Specifically, the treatment effect for Guangdong represents the weighted average of the provincial ETS impact and Shenzhen’s municipal effects. Despite this limitation, we use this approach because excluding Shenzhen or Guangdong would substantially reduce our sample’s economic relevance, given the region’s significant share in China’s industrial activity and carbon emissions.

Therefore, our final treatment group comprises six province-level ETS pilots: Beijing, Shanghai, Tianjin, Chongqing, Hubei, and Guangdong (including Shenzhen). The control group comprises 24 province-level regions, excluding Hong Kong, Macau, and Tibet owing to data availability constraints and distinct administrative systems.

4.2. Econometric specifications

The DDD estimation specification is as follows:

$$Y_{icmt} = \alpha + \beta(Pilot_c \times Industry_m \times Post_t) + \eta_{cm} + \theta_{ct} + \gamma_{mt} + \varphi W_{icmt} + \varepsilon_{icmt}, \quad (1)$$

where the subscripts i , c , m , and t denote firms, provinces, industries, and years, respectively. We examine two primary outcome variables that capture the different dimensions of offshoring behavior. First, Y_{icmt} represents the number of *offsite* subsidiary firms established by parent company i in province c and year t , reflecting the extent of offshoring investment. Second, Y_{icmt} measures the average registered capital of subsidiary firms, reflecting the depth of offshoring investment. The key independent variable in our specification is the interaction between the three indicator terms, $Pilot_c$, $Industry_m$, and $Post_t$. The coefficient of interest, β , represents the average treatment effect of ETS implementation on regulated firms’ offshoring activity.

Our specification includes a comprehensive set of fixed effects: η_{cm} , θ_{ct} , and γ_{mt} are the province-industry, province-year, and industry-year fixed effects, respectively. We also control for time-varying firm characteristics via the variable

W_{icmt} , which may influence investment decisions, including firm age, profitability, and ownership type. Detailed definitions and summary statistics for these variables are provided in Section 3. To deal with potential heteroscedasticity and serial correlation, we use the province-industry level to cluster standard errors.

4.3. Extensions and heterogeneity

We extend the baseline specification in two ways. First, to examine the role of the carbon market, we incorporate carbon prices across the pilot regions.

$$Y_{icmt} = \alpha + \beta_1(Pilot_c \times Industry_m \times Post_t) + \beta_2(Pilot_c \times Industry_m \times Post_t \times Price_{ct}) + \eta_{cm} + \theta_{ct} + \gamma_{mt} + \phi W_{icmt} + \varepsilon_{icmt}, \quad (2)$$

where $Price_{ct}$ represents the annual average carbon price in province c and year t . The coefficient β_2 captures the additional offshoring response to carbon price levels. A positive β_2 would indicate that higher carbon prices increase the number of subsidiary firms in non-ETS regions, consistent with the PHH.

Second, we investigate how firms' existing environmental capabilities affect their responses to the pilot ETS by identifying environmentally advanced firms through China's green factory certification program.

$$Y_{icmt} = \alpha + \beta_1(Pilot_c \times Industry_m \times Post_t) + \beta_3(Pilot_c \times Industry_m \times Post_t \times Green\ factory_i) + \eta_{cm} + \theta_{ct} + \gamma_{mt} + \phi W_{icmt} + \varepsilon_{icmt}, \quad (3)$$

where $Green\ factory_i$ equals 1 if a parent firm or any of its subsidiaries obtain an official green factory certification during our sample period. The coefficient β_3 reveals whether environmentally capable firms respond differently to ETS implementation. A negative β_3 would suggest that firms with established green technologies face lower marginal costs of domestic emissions reduction, potentially reducing their incentives to offshore production.

4.4. Identification validity and robustness

The credibility of our DDD strategy depends on the parallel trend assumption that the treatment and control groups follow similar trends in the absence of ETS implementation. To validate this assumption, we conduct a series of complementary analyses, as illustrated in Figures 3–6.

Figure 3 shows that, prior to ETS implementation, the trends in offsite subsidiary

establishment were similar across targeted and non-targeted industries in the pilot and non-pilot provinces. This finding supports the validity of our identification strategy. Notably, while all groups show modest growth in subsidiary establishment before the ETS implementation, the treatment group exhibits a significant increase after 2013, suggesting a clear policy response.

We conduct two complementary event studies to highlight why a DID approach is insufficient for identifying the causal effects of ETS implementation. Figure 4 presents a traditional DID estimate comparing pilot and non-pilot provinces, which compares Groups A + B versus Groups C + D in Figure 2. The statistically nonsignificant result highlights a key limitation of this approach: by including non-targeted industries not affected by the policy in the treatment group, the DID method results in undervaluation. Figure 5 presents a placebo event study that compares non-targeted industries in the pilot and non-pilot provinces (i.e., Group B versus Group D), which indicates a significant subsidiary establishment after 2013, implying that policies such as the Air Pollution Prevention and Control Action Plan also had a positive effect. Thus, excluding non-target industries from the control group could introduce bias and undermine causal inferences. Meanwhile, Figure 6, a DDD event study that compares Group A minus Group B versus Group C minus Group D, differences out the region-wide policy effect and then isolates the ETS-specific effect. The flat pre-trends and dynamic evolution of the treatment effects post-2013 provide supporting evidence that our DDD strategy identifies the causal impact of ETS implementation on firm behavior.

The validity of our DDD approach also relies on control groups that provide credible counterfactuals. Our rich set of fixed effects addresses this requirement by controlling for province-year, province-industry, and industry-year variations. Therefore, we can control for all time-varying and time-invariant provincial characteristics, such as regional spillovers, agglomeration, corruption, and local political activism. We can also control for all time-varying and time-invariant industry characteristics such as changes in technology and industry policies.

We conduct a set of sensitivity analyses to establish the robustness of the findings. First, we estimate models with province-specific industry coverage to account for

heterogeneous policy implementation. Second, we examine the policy impacts on firms' domestic and international subsidiaries to study the spatial patterns of leakage. Third, we explore the differential effects across firm types, including factor intensity, technological sophistication, pollution intensity, and geographic location. These analyses provide a comprehensive assessment of the robustness of our main findings and help identify the mechanisms driving firms' responses to environmental regulations.

5. Empirical results

5.1. Main results

Our empirical analysis examines how firms respond to the pilot ETS through two key measures: the number of subsidiary firms established in non-ETS regions and their average investment scales. Table 3 presents the DDD estimation results for the number of established subsidiaries. Column 1 shows the baseline regression (Equation 1), where we find a positive and statistically significant coefficient for the triple interaction term. This indicates that firms in targeted industries in ETS regions tend to establish subsidiary firms in regions with less stringent environmental regulations (i.e., where the pilot ETS has not been implemented), confirming the PHH.

Column 2 incorporates the carbon price variations into the analysis (Equation 2). While the baseline triple interaction coefficient becomes negative and nonsignificant, the interaction with carbon price is positive and significant. This finding implies that higher carbon prices strengthen firms' incentives to relocate to nonregulated regions. The total effect becomes positive when the carbon price exceeds 4.20 yuan/ton, which is well below the average price of each pilot ETS. This suggests that the relocation effect persists across different price levels.

Column 3 examines whether green manufacturing capabilities influence firms' responses to the ETS by further interacting the triple difference term with a green factory indicator (Equation 3). The coefficient on the ETS effect (β_1) becomes small but remains weakly significant (p -value = 0.107) when including this interaction. The new term does not have a negative coefficient; thus, green factories' behavior is not significantly different from that of others.

The asset–liability ratio shows a positive coefficient, indicating that firms with higher financial performance are more likely to set up subsidiaries in non-ETS regions. Fixed assets have a negative coefficient, suggesting that firms with substantial fixed investments face higher relocation costs and are less likely to establish subsidiaries in non-ETS areas. The number of employees has a positive impact, implying that larger firms have greater resources and capacity to engage in relocation. By contrast, state ownership has a negative relationship with relocation activities. This finding can be attributed to the fact that SOEs are highly controlled by governments, and important decisions, such as opening and closing, are strongly influenced by administrative orders rather than by general managers (Cai et al., 2016).

Table 4 uses the average investment value as the dependent variable, revealing a contrasting pattern regarding the investment depth of these subsidiaries. The triple interaction coefficient is negative and significant, suggesting that although regulated firms establish more subsidiaries in non-ETS regions, these subsidiaries tend to be smaller in scale. This can be attributed to several factors. First, under the ETS, firms may prefer to establish multiple smaller subsidiaries over fewer large ones as smaller units provide more flexibility to adjust operations or exit the market, if needed. Second, the ETS increases operating costs in regulated regions, encouraging firms to reallocate capital for more efficient use. Third, having multiple smaller units allows firms to preserve their flexibility in future decisions. The effect persists when considering either carbon price variations or the green factory factor, with the baseline triple interaction term remaining negative and significant in Columns 2 and 3.

In contrast to the number of subsidiary firms, the asset–liability ratio and fixed assets do not have a significant impact on the average investment scale of subsidiary firms. The number of employees has a consistent and positive impact. However, we find that state ownership has a positive relationship with investment by subsidiary firms, possibly because China’s financial system privileges SOEs through bank credit allocation and bond market access, where SOEs can obtain low-cost, long-term capital compared with private enterprises (Lin & Milhaupt, 2017).

5.2. Robustness checks

We conduct a robustness check to validate our main findings. We address the potential heterogeneity in industry targeting under the pilot ETS across regions. While our baseline analysis employed nationally defined targeted industries, the actual implementation of the ETS varied substantially at the provincial level. To capture the institutional differences more precisely, we reconstruct our treatment variable using province-specific industry classifications (detailed in Appendix Table A2). The results in Table 5 are qualitatively similar to those in Table 3.

Additionally, we conduct a placebo test to examine whether the pilot ETS affects firms' choice of the subsidiary establishment in foreign countries or in the same regions as the parent firm. Table 6 shows that the triple interaction term is not statistically significant for foreign countries or the same regions, suggesting that firms do not significantly increase their investments abroad or within the same location as the parent firm in response to ETS implementation. This indicates that regulatory pressures, rather than location-specific factors, primarily drive firms' relocation decisions.

5.3. Heterogeneous effects

The heterogeneity analysis in Table 7 reveals important variations in firms' responses to the pilot ETS across different characteristics.

Factor intensity: While the results are not statistically significant, capital-intensive firms exhibit relatively stronger relocation effects than labor- or technology-intensive firms. This suggests that firms with higher levels of physical capital may have greater flexibility in relocating their operations.

Technological sophistication: The contrast between high-tech and non-high-tech firms is particularly large, with high-tech firms showing almost no relocation responses (-0.029 , nonsignificant) and non-high-tech firms showing a strong positive response (14.373 , significant at the 5% level). This finding indicates that technology enables firms to adapt to environmental regulations without the need to relocate.

Pollution intensity: High-polluting firms demonstrate the strongest relocation response (17.926 , significant at the 5% level), whereas non-high-polluting firms show a minimal response (-0.950 , nonsignificant). This finding aligns with the expectation that pollution-intensive firms have stronger incentives to avoid environmental

regulations.

Geographic location: The regional heterogeneity analysis reveals that firms in western regions show the largest relocation response, followed by those in eastern regions. Conversely, firms in middle regions exhibit a negative response. This pattern may reflect the differences in regional economic development.

These heterogeneous effects highlight the importance of considering firm characteristics and regional factors when designing environmental policies. These findings suggest that policies that promote technological advancement and support regional economic development may reduce the PHH effects of environmental regulations.

6. Conclusion and policy implications

In this study, we investigate the PHH using a DDD estimation approach, where we compare the behavior of targeted industries in regions covered by the ETS with three control groups: untargeted industries in ETS regions, targeted industries in non-ETS regions, and untargeted industries in non-ETS regions before and after policy implementation.

By using comprehensive firm-level panel data from the CSMAR database, we find that firms would increase their number of subsidiaries in unregulated regions, confirming the PHH. Interestingly, we also find that firms reduce the average investment scale of their offsite subsidiaries, possibly because of risk management and resource relocation. The results are robust to a series of robustness checks for identifying assumptions and other economic concerns. Furthermore, we find that firms with higher carbon prices reallocate more subsidiaries to non-ETS regions.

We propose the following policy recommendations. First, under the already established nationwide carbon market, a cross-regional coordination mechanism can be implemented in which provincial emission caps and parent company allowances are linked to curb emission transfers through the offsite subsidiary establishment. Second, because the carbon price serves as an important signal of firms' behavior, the government can rely on market mechanisms for optimal firm relocation. Third, our

heterogeneity analyses suggest that targeted policy tools, such as fiscal incentives and technological upgrade support, can reduce pollution haven behavior more effectively.

Acknowledgement

This research was supported by the Kyoto University Faculty of Agriculture fund for Education and Research.

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Table 1. Annual online quota transaction volume, price, and value by carbon market since its opening in 2020

Location of market	Start date	Total volume (million tons)	Average price (yuan/ton)	Total value (million yuan)
Beijing	Nov 28, 2013	16.40	56.42	1037
Shanghai	Nov 26, 2013	17.78	30.71	546
Tianjin	Dec 26, 2013	18.66	21.96	410
Chongqing	Jun 19, 2014	9.71	18.28	66
Guangdong	Dec 19, 2013	176.02	20.56	3619
Hubei	Apr 02, 2014	76.37	22.99	1756
Shenzhen	Jun 18, 2013	49.21	24.08	1185

Notes: Daily transaction data are collected from each pilot ETS online transaction platform. The annual data are calculated by the author.

Table 2. Definition of variables and summary statistics

Variable	Mean	Std. dev.	Min	Max	Description
The number of subsidiary firms	7.36	19.66	0	712	The number of offsite subsidiary firms
Log (the average scale of sub firm)	11.24	8.85	0	28.71	Log of (Sum of registered capital of all offsite subsidiary firms in Chinese Yuan)
Asset-liability ratio	0.54	0.52	0.01	27.92	The percentage of liabilities to assets (%)
Fixed assets	0.24	0.18	0	0.96	Fixed assets/total assets (%)
Log (Employee)	7.76	1.47	2.19	12.84	Log of the number of total employees
State-owned	0.60	0.49	0	1	=1 if it is state-owned; =0 otherwise
Firm age	24.64	4.01	13	42	The age of the parent firm in 2020 (years)
Pilot	0.38	0.48	0	1	=1 if it is a pilot region; =0 otherwise
After	0.57	0.49	0	1	=1 if year $\geq$ 2013; =0 otherwise
Industry	0.25	0.43	0	1	=1 if it is a targeted industry under ETS; =0 otherwise
Carbon Price	7.64	17.39	0	89.50	Annual average carbon price weighted by transaction volume (Yuan/ton)
Green factory	0.25	0.43	0	1	=1 if the parental firm has a green factory; =0 otherwise

Data source: Price data are calculated based on each pilot ETS online transaction platform, green factory data are collected from the Green Factory List by the Chinese government, and other variables are collected from the CSMAR database.

Table 3. Results of the triple difference analysis explaining the impact of pilot ETS on the number of offsite subsidiary firms

	(1) Baseline model	(2) Carbon price model	(3) Green factory model
Pilot*Industry*After	7.121 ** (2.06)	-1.026 (-0.34)	6.668 (1.62)
Pilot*Industry*After*carbon price		0.244 ** (2.00)	
Pilot*Industry*After*green factory			1.481 (0.77)
Asset-liability ratio	1.192 *** (3.10)	1.202 ***** (3.10)	1.193 *** (3.11)
Fixed assets	-9.874 *** (-3.84)	-9.841 *** (-3.82)	-9.869 *** (-3.84)
Log (Employee)	4.556 *** (5.50)	4.557 *** (5.50)	4.548 *** (5.46)
Firm age	0.038 (0.40)	0.037 (0.39)	0.039 (0.41)
State-owned	-3.237 *** (-2.85)	-3.252 *** (-2.86)	-3.222 *** (-2.82)
Province-year fixed effect	Yes	Yes	Yes
Province-industry fixed effect	Yes	Yes	Yes
Industry-year fixed effect	Yes	Yes	Yes
Observations	15,009	15,009	15,009
R ²	0.414	0.415	0.414

Notes: (1) This table shows the effect of the pilot ETS on firms' relocation to unregulated regions. The dependent variable is the number of offsite subsidiary firms in non-ETS regions.

(2) We estimate Equation (1) in Column (1), Equation (2) in Column (2), and Equation (3) in Column (3). Price refers to the annual average carbon price of province c in year t . Green factory is a dummy variable that equals 1 when the parent firm has a green factory. Green factories refer to factories that achieve intensive land use, clean production, waste recycling, and low-carbon energy consumption, as announced by the Ministry of Industry and Information Technology of China.

(3) t -values are shown in parentheses. ** Significant at the 5% level. *** Significant at the 1% level.

Table 4. Results of the triple difference analysis explaining the impact of pilot ETS on the average investment value of offsite subsidiary firms

	(1) Baseline model	(2) Carbon price model	(3) Green factory model
Pilot*Industry*After	-2.460 ** (-2.38)	-2.851 ** (-2.51)	-2.628 ** (-2.06)
Pilot*Industry*After*carbon price		0.012 (0.46)	
Pilot*Industry*After*green factory			0.549 (0.16)
Asset-liability ratio	-0.274 (-1.26)	-0.273 (-1.26)	-0.273 (-1.26)
Fixed assets	-1.253 (-0.84)	-1.251 (-0.84)	-1.251 (-0.84)
Log (Employee)	1.218 *** (7.24)	1.218 *** (7.24)	1.215 *** (7.29)
Firm age	0.065 (1.18)	0.065 (1.17)	0.065 (1.18)
State-owned	0.955 * (1.95)	0.954 * (1.95)	0.960 ** (1.98)
Province-year fixed effect	Yes	Yes	Yes
Province-industry fixed effect	Yes	Yes	Yes
Industry-year fixed effect	Yes	Yes	Yes
Observations	15,009	15,009	15,009
R ²	0.411	0.411	0.411

Notes: (1) In this table, we show the effect of the pilot ETS on firms' investments in unregulated regions. The dependent variable is the investment amount per subsidiary firm in non-ETS regions.

(2) We estimate Equation (1) in Column (1), Equation (2) in Column (2), and Equation (3) in Column (3). Price refers to the annual average carbon price of province c in year t . Green factory is a dummy variable that equals 1 when the parent firm has a green factory. Green factories refer to factories that achieve intensive land use, clean production, waste recycling, and low-carbon energy consumption, as announced by the Ministry of Industry and Information Technology of China.

(3) t -values are shown in parentheses. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 5. Results of the triple difference analysis explaining the impact on the province-specific targeted industries under ETS on the number of offsite subsidiary firms

	(1) Baseline model	(2) Carbon price model	(3) Green factory model
Pilot*Industry*After	4.415 ** (2.23)	-1.996 (-0.99)	4.258 * (1.75)
Pilot*Industry*After*carbon price		0.197 ** (2.21)	
Pilot*Industry*After*green factory			0.452 (0.20)
Asset-liability ratio	1.206 *** (3.09)	1.216 *** (3.10)	1.206 *** (3.10)
Fixed assets	-9.784 *** (-3.80)	-9.882 *** (-3.85)	-9.789 *** (-3.81)
Log (Employee)	4.553 *** (5.50)	4.557 *** (5.50)	4.549 *** (5.45)
Firm age	0.040 (0.42)	0.039 (0.42)	0.041 (0.43)
State-owned	-3.265 *** (-2.86)	-3.262 *** (-2.86)	-3.263 *** (-2.86)
Province-year fixed effect	Yes	Yes	Yes
Province-industry fixed effect	Yes	Yes	Yes
Industry-year fixed effect	Yes	Yes	Yes
Observations	15,009	15,009	15,009
R ²	0.414	0.416	0.414

Notes: (1) In this table, we set targeted industries differently for each pilot province and show the effect of the pilot ETS on firms' relocation to unregulated regions. We keep the other variables consistent with those in Table 4.

(2) *t*-values are shown in parentheses. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 6. Placebo regressions testing the impact of ETS on foreign and local subsidiary

firms

Dependent variable:	(1) Foreign subsidiary firms	(2) Subsidiary firms in the same region as the parent firm
Pilot*Industry*After	0.615 (0.62)	0.791 (0.58)
Asset-liability ratio	0.391 *** (3.09)	1.058 *** (3.40)
Fixed assets	-2.372 ** (-2.54)	-10.768 *** (-5.29)
Log (Employee)	1.455 *** (7.16)	3.703 *** (7.04)
Firm age	0.054 (0.92)	0.109 (1.28)
State-owned	-0.769 * (-1.85)	0.828 (0.78)
Province-year fixed effect	Yes	Yes
Province-industry fixed effect	Yes	Yes
Industry-year fixed effect	Yes	Yes
Observations	15,009	15,009
R ²	0.346	0.477

Notes: (1) This table shows the effects of the pilot ETS on firms' relocation to foreign countries in Column (1) and whether parent firms increase the number of local subsidiary firms in Column (2).

(2) *t*-values are shown in parentheses. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Table 7. Heterogeneous effects of the pilot ETS by firm characteristics

Dependent variable: number of subsidiary firms	Pilot*Industry*After coefficient	Observations
<i>Factor Intensity</i>		
Labor-intensive	5.966 (1.43)	6,904
Technology-intensive	5.599 (1.14)	4,688
Capital-intensive	8.403 (1.28)	2,995
<i>Technology Sophistication</i>		
High-tech	-0.029 (-0.02)	6,846
Non-high-tech	14.373 ** (2.06)	8,154
<i>Pollution Intensity</i>		
High-pollution	17.926 ** (2.36)	3,881
Non-high-pollution	-0.950 (-0.24)	11,093
<i>Geographic Location</i>		
East	7.219 * (1.74)	9,363
Mid	-4.459 (-1.33)	2,907
West	22.272 ** (1.98)	2,351

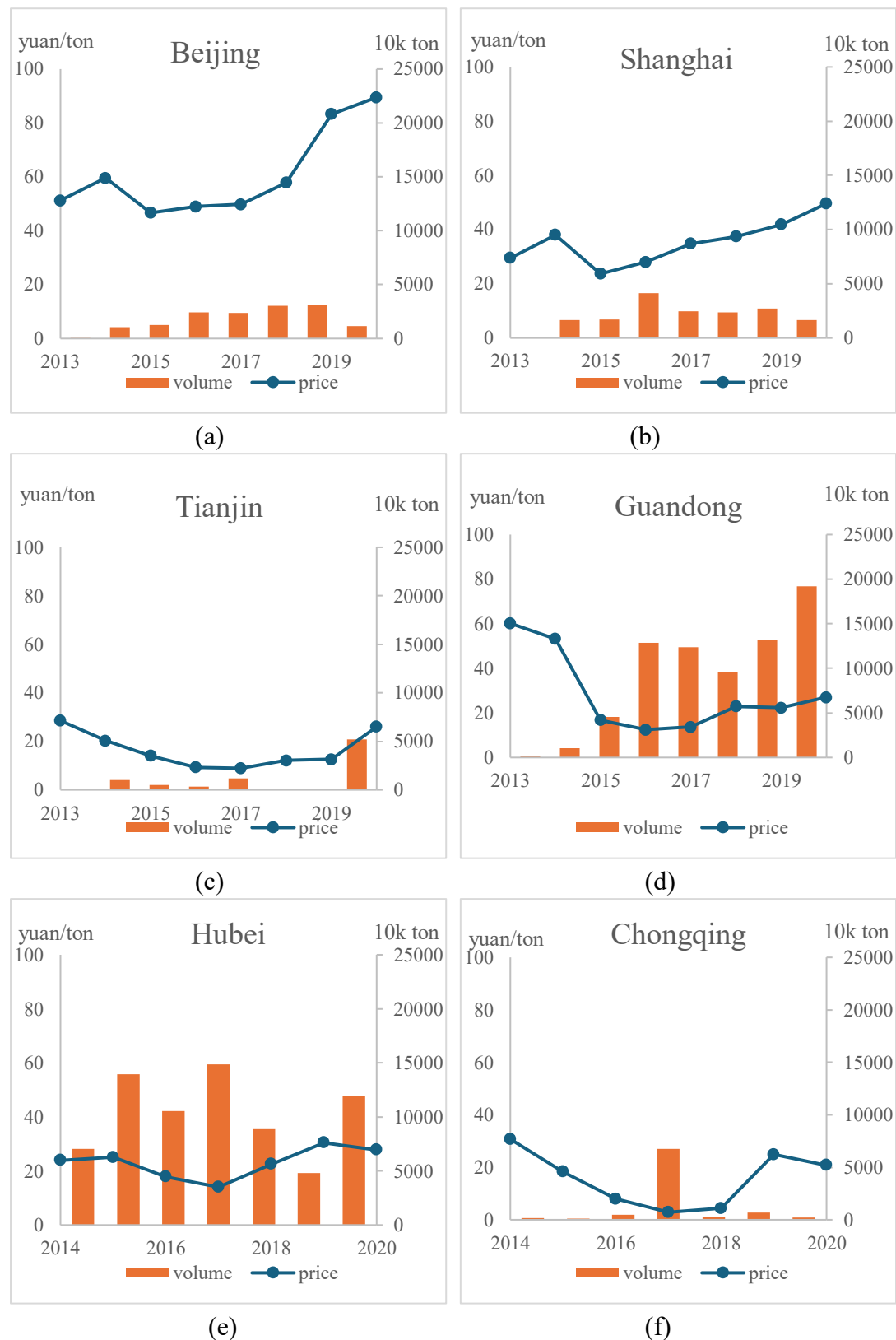
Notes: (1) This table shows the effects of the pilot ETS by firm type. We conduct four groups of heterogeneity checks. The first group splits the sample into labor-, technology-, and capital-intensive firms (Yin et al, 2018). The fixed asset ratio (net fixed assets/average total assets) and R&D expenditure-to-payroll ratio (R&D expenditure/payable employee salaries) are used to categorize industries. First, according to the fixed asset ratio, industries with larger ratios are classified as capital intensive, indicating that the capital is more important to them. Second, according to the R&D expenditure-to-payroll ratio, industries with a higher ratio indicate that technology R&D is more important than labor factors for enterprises and, thus, belong to technology-intensive industries, with the rest belonging to labor-intensive industries. The second group splits the sample into high- and non-high-technique firms (Yang & Zhou, 2020). According to the classification guidelines for listed companies in China issued by the China Securities Regulatory Commission in 2012, companies with classification codes C25–C29, C31–C32, C34–C41, I63–I65, and M73 are defined as high-tech industry companies. The third group splits the sample into high- and non-high-pollution firms (Wang & He, 2021). According to the secondary industry classification revised by the China Securities Regulatory Commission in 2012, the 15 heavily polluting industries are defined as follows: B06 Coal Mining and Washing; B07 Oil and Natural Gas Extraction; B08 Ferrous Metal Mining; B09 Non-Ferrous Metal Mining; C17 Textile Industry; C19 Leather, Fur,

Feather and Related Products, and Footwear Industry; C22 Paper and Paper Products Industry; C25 Oil Processing, Coking, and Nuclear Fuel Processing Industry; C26 Chemical Raw Materials and Chemical Products Manufacturing; C28 Chemical Fiber Manufacturing; C29 Rubber and Plastic Products Industry; C30 Non-Metallic Mineral Products Industry; C31 Ferrous Metal Smelting and Rolling Processing Industry; C32 Non-Ferrous Metal Smelting and Rolling Processing Industry; D44 Electricity and Heat Production and Supply Industry. The fourth group splits the sample into three regions: east, middle, and west (Shen et al, 2021). The eastern group includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The middle group includes Shanxi, Jilin, Heilongjiang, Henan, Hubei, Hunan, Anhui, and Jiangxi. The western group includes Inner Mongolia, Chongqing, Sichuan, Guangxi, Guizhou, Yunnan, Shanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

(2) The covariates in the previous regression analyses, province-industry fixed effects, industry-year fixed effects, and province-year effects are controlled, and the standard errors are clustered at the province-industry level.

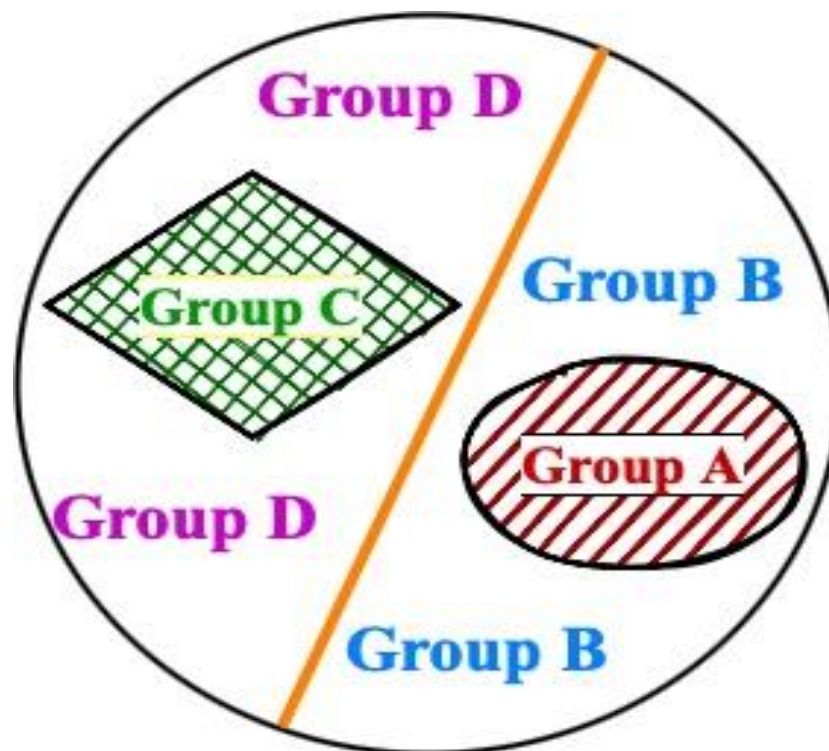
(3) t -values are shown in parentheses. *Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

Figure 1. Annual average carbon price and total transacted volume by each pilot ETS market



Notes: These figures show the total transacted volume and annual average carbon price by pilot ETS market during the sample period (2013–2020) and in Hubei and Chongqing from 2014. Annual data are calculated based on each pilot ETS online transaction platform.

Figure 2. Triple difference group classification



Notes: (1) This graph is drawn by the author using drawio.

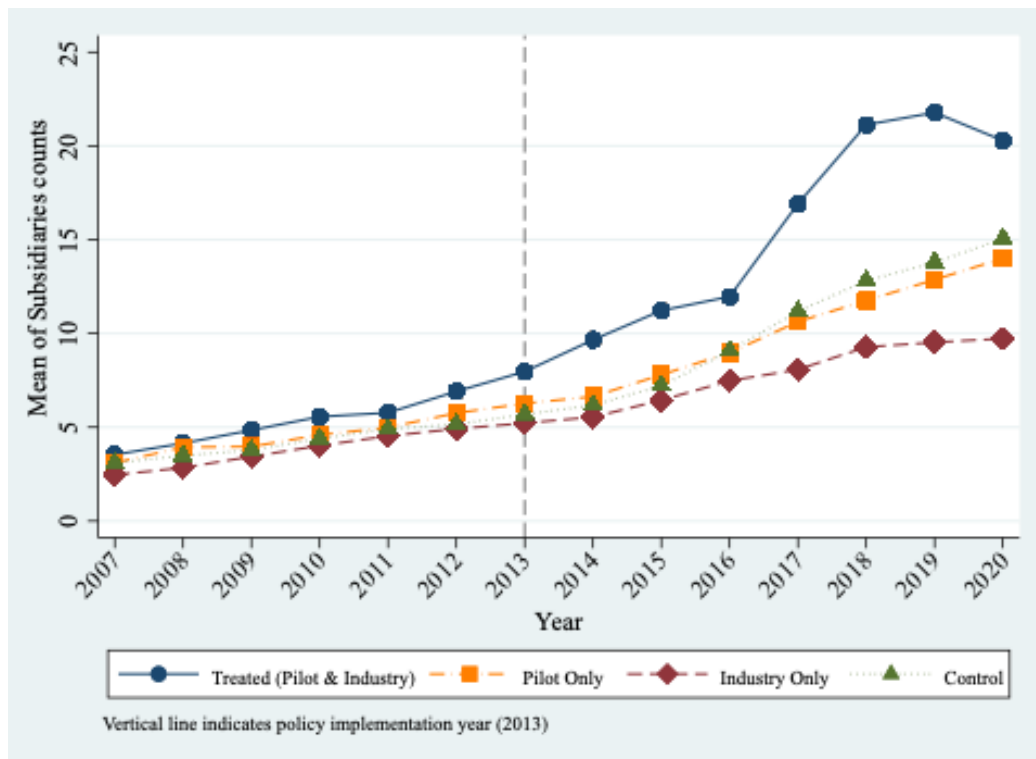
(2) Group A refers to the group where pilot = 1 and targeted industry = 1.

Group B refers to the group where pilot = 1 and targeted industry = 0.

Group C refers to the group where pilot = 0 and targeted industry = 1.

Group D refers to the group where pilot = 0 and targeted industry = 0.

Figure 3. Parallel trend of the number of offsite subsidiary firms in a triple difference analysis, comparing targeted industries in pilot provinces vs. non-targeted industries in non-pilot provinces



Notes: (1) In this figure, we show parallel trends for the DDD analysis.

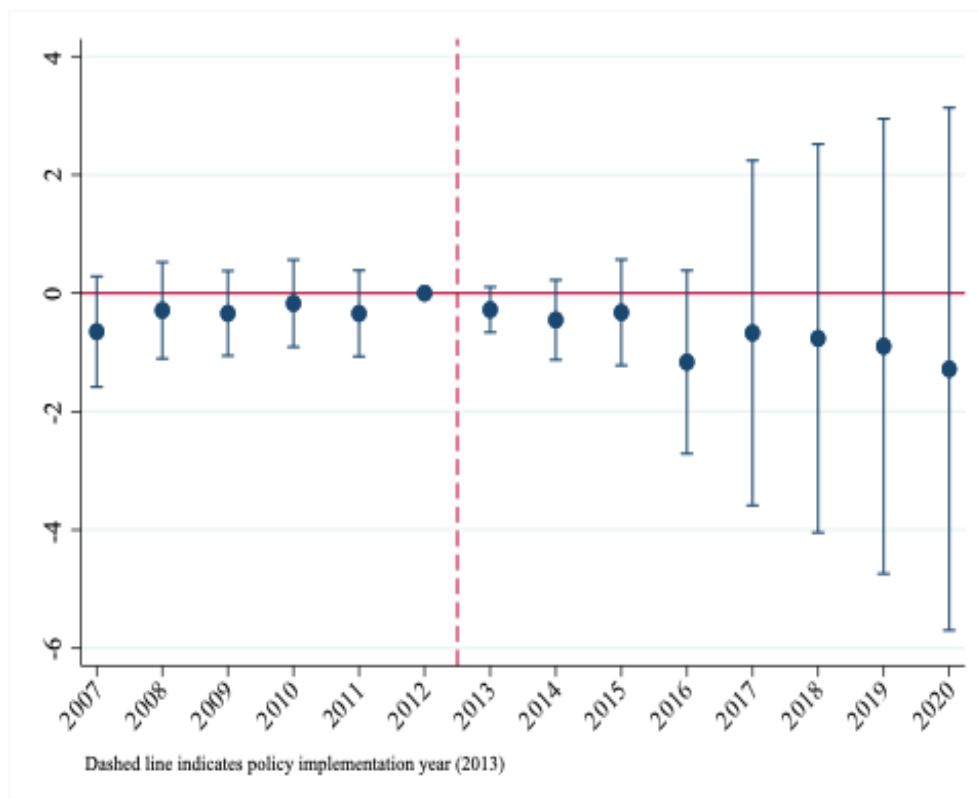
(2) Treated refers to the group in which pilot = 1 and targeted industry = 1 (Group A).

Pilot only refers to the group where pilot = 1, which covers Group A + B.

Industry only refers to the group where targeted industry = 1, which covers Group A + C.

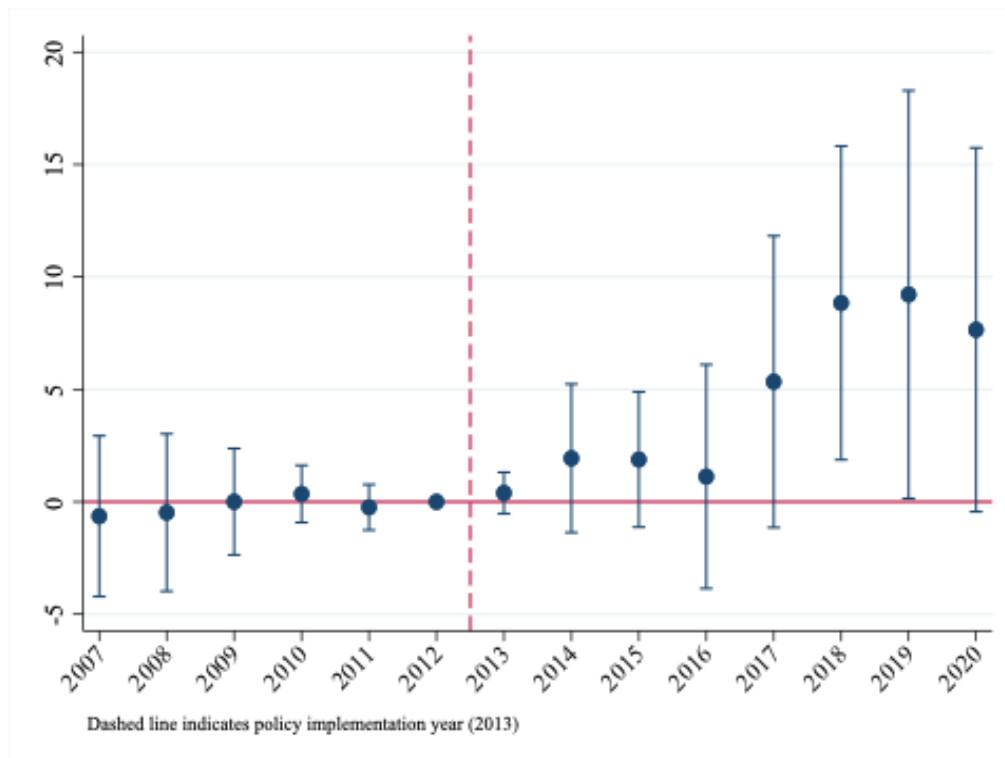
Control refers to the group where pilot = 0 and targeted industry = 0, which includes Group D.

Figure 4. Event study comparing pilot versus non-pilot provinces



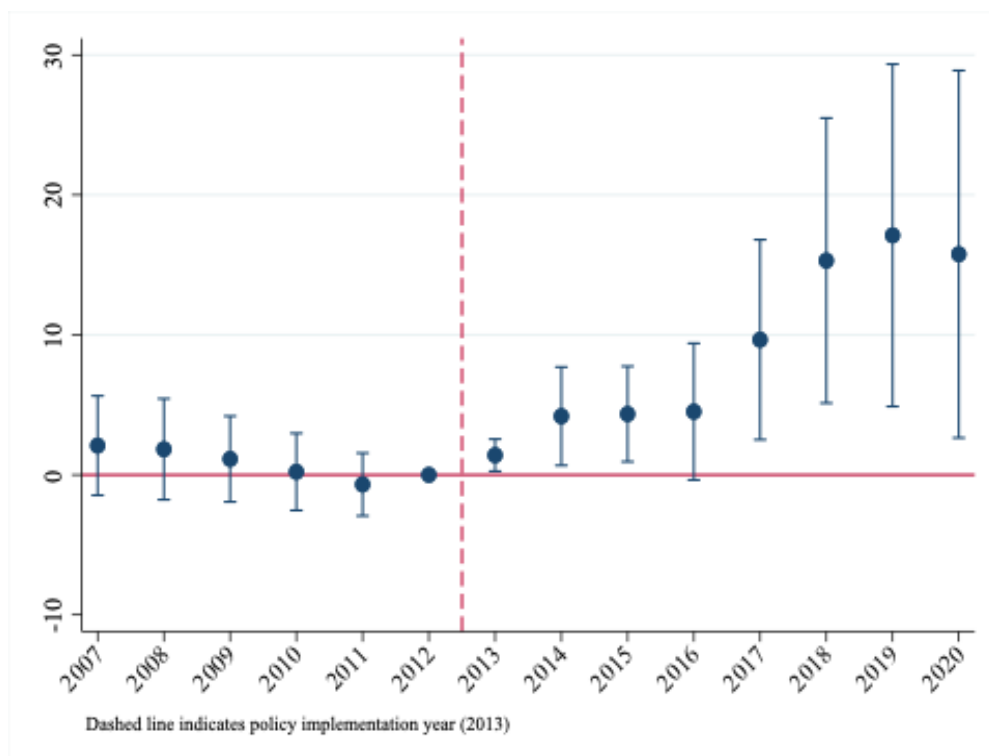
Notes: In this figure, we show the event study comparing pilot provinces with non-pilot provinces. The figure reports the point estimates and 90% confidence intervals.

Figure 5. Placebo event study explaining non-targeted industries in pilot versus non-pilot provinces



Notes: In this figure, we show the event study to compare non-targeted industries in pilot provinces and non-targeted industries in non-pilot provinces.

Figure 6. Triple difference event study



Notes: This figure shows the event study of the DDD analysis, comparing targeted industries in pilot provinces with non-targeted industries in non-pilot provinces. This figure shows the test results for the parallel pre-trend assumption.