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Climate Policy and Carbon Leakage: Evidence from Investment Relocation of Chinese Corporations

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1 Introduction

The issue of global warming is becoming increasingly severe. Reducing greenhouse gas emissions and achieving carbon neutrality have emerged as a shared global concern. Climate change is ostensibly an environmental issue, but it is emerging as a serious business issue and even a matter of global economic development (Gardiner, 2004). The carbon emissions problem has become a key focus. As countries worldwide strive to address the escalating impacts of climate change, there is an urgent need for effective emission reduction strategies.

Within the framework of macroeconomic accounting, emissions permits are defined as a form of intangible non-produced assets (OECD, 2008). Essentially, it refers to the government-granted right for corporations and organizations to emit a specified quantity of greenhouse gases during production activities, thereby representing an extension of natural resource utilization rights under the framework of environmental governance. In this context, the carbon emissions trading system (ETS) has emerged as a crucial market-based mechanism for reducing greenhouse gas emissions. As of 2024, there are 36 ETSs in force around the world, with another 22 at various stages of consideration and development. They cover 18% of carbon emissions worldwide. Carbon taxes and ETSs currently being considered could further expand coverage to almost 30%, but this will require strong political commitment (International Carbon Action Partnership, 2024; World Bank, 2024).

As the world's largest emerging economy and a major carbon emitter (International Energy Agency, 2024), China has played an active role in international climate agreements and consistently pursued green innovation (Harrison et al., 2017) and low-carbon development that balances economic growth with environmental sustainability. Since 2011, China has established eight pilot carbon markets. Following the pilot phase, China's national ETS was officially launched in 2021. Regional pilot ETSs currently operate in parallel with the national ETS, but will gradually be integrated into one unified and efficient carbon trading system (Li et al., 2022). The national ETS has now completed the first two compliance cycles, creating a new market for domestic emission reduction projects. In 2024, the China Certified Emission Reduction (CCER) market was launched in Beijing, accompanied by the introduction of several significant regulations and

policies to strengthen the system's foundation. China's ETS is currently at a vital stage of development, progressing from regional pilot schemes to systematic expansion and maturation, which makes it a valuable subject for academic and policy-oriented research.

The ETS increases the marginal cost of emissions by enforcing caps and pricing mechanisms, leading regulated firms to face trade-offs between expensive abatement efforts and permit purchases. In addition, regulated firms may lose market share to rival firms outside the ETS (Martin et al., 2016). These financial pressures often result in strategic shifts in global operations and investment decisions. Unilateral and geographically bounded policies may raise domestic production costs (Naegele & Zaklan, 2019), potentially triggering investment relocation. In such cases, carbon-intensive firms may shift high-emission production activities or new capacity to countries or regions with more lenient carbon regulations. This can result in carbon leakage, thereby weakening the effectiveness of domestic climate policy efforts. From another perspective, rising carbon costs and policy uncertainty may reduce the willingness and capacity of some firms to expand internationally, especially those with limited operational flexibility or insufficient experience managing cross-border activities. Instead, these firms may choose to allocate their limited resources toward meeting domestic green transition requirements (Hendrichs & Busch, 2012). At the same time, another pathway of corporate response emerges: firms with green technological and managerial advantages may leverage outbound foreign direct investment (OFDI) as a strategic means to enter low-carbon markets and export their green capabilities. In doing so, they not only enhance international competitiveness and contribute to environmental benefits through technology spillovers but may also reinforce their green innovation efforts by accessing new knowledge, markets, and regulatory frameworks. This form of “green OFDI” illustrates how firms' internationalization strategies can evolve in response to tightening carbon constraints (Lema et al., 2020; Long et al., 2023).

The purpose of the study is to explore the impact of China's national ETS on corporate OFDI activities. It seeks to understand the dynamic interplay between climate policy and international investment at the firm level. The empirical analysis is based on panel data from 2017 to 2023 and adopts a two-step identification strategy. First, propensity score matching is used to construct a comparable control group based on pre-policy firm characteristics. This is followed by a

difference-in-differences model to estimate the causal impact of the ETS. The main results show that the policy significantly reduces firms' OFDI. A triple-differences model further indicates that this negative effect is weaker for investments in Belt and Road Initiative countries, suggesting that national development strategies may help buffer climate policy constraints

In contributing to the broader discourse on climate policy and international investment, this study offers three distinct insights. First, it provides the first firm-level empirical evidence on how China's national ETS influences corporate OFDI, advancing the understanding of carbon leakage beyond the regional settings. Second, it provides indicative evidence of the mechanisms underlying firms' strategic responses, showing that regulatory uncertainty and limited internal capabilities tend to discourage international expansion rather than trigger investment relocation in China. Third, it demonstrates that national development initiatives, such as the Belt and Road Initiative, can reduce the restrictive effects of environmental regulation. These insights highlight the importance of coordinated policy design in reconciling climate objectives with outward investment under the green transition.

This study is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the data sources and empirical methodology, with a focus on sample selection, variable definitions and model construction. Section 4 presents and discusses the empirical results. Section 5 concludes with key findings, gives policy implications, and provides directions for future research.

2 Literature Review

2.1 Operating Mechanisms of ETS in China

Through years of experimentation, from regional pilots to a national carbon market, China has steadily improved its ETS framework. Existing research has provided a comprehensive understanding of China's regional ETS experiences by focusing on the design and implementation of pilot ETS programs at the provincial and municipal levels, offering valuable policy lessons for the national ETS. Scholars have focused on three core elements of China's ETS: cap setting, allowance allocation, and carbon pricing. These three components determine the structure and effectiveness of the system.

Cap setting establishes the overall emissions ceiling within the ETS, serving as the foundation for the total supply of tradable allowances in the market. Liu et al. (2022) pointed out that most of China's regional pilot ETS programs adopted intensity-based caps, which set carbon intensity requirements for firms without imposing strict limits on total emissions. This design was consistent with the initial design of the EU ETS and reflected China's commitment to balancing environmental and economic development. Considering regional disparities as a key factor in national energy and climate policymaking, Zhang et al. (2013) developed a global computable general equilibrium (CGE) model with regional detail to assess the implications of CO₂ intensity targets across China. Similarly, Feng et al. (2018) used the CGE model to simulate ETS linkages between Hubei and Guangdong, and suggested that emission caps should be more flexible in carbon-intensive or less-developed regions.

Allowance allocation refers to how emission permits are distributed among regulated firms, directly affecting compliance costs and market incentives. In China, free allocation remains dominant, primarily implemented through benchmarking. Cong and Wei (2010) employed an agent-based model and found that output-based allocation was more effective in reducing emissions within the power sector. Wang et al. (2014) developed a hybrid nonlinear grey prediction and quota allocation model to support optimal planning of carbon intensity reduction targets at both the sectoral and provincial levels. Xu et al. (2015) proposed a three-level decision

model for allowance allocation policy-making. Zhu et al. (2015) developed a fuzzy stochastic programming model to help plan municipal electricity system under uncertainty of carbon trading in Beijing. Many scholars argued that the auction should gradually replace free allocation as the ETS matures. Li et al. (2019) applied a dynamic CGE model to evaluate different revenue recycling options and identified the most suitable mechanism for China's long-term ETS development. In addition, Chen et al. (2023) designed a blockchain-based carbon allowance auction framework to enhance transparency and efficiency in the carbon trading process.

Carbon pricing captures the market-determined value of emission allowances and functions as a central signal. Fan and Todorova (2017) empirically analyzed carbon prices in four pilot ETSs in China, linking them to macro-financial risks and market sentiment, and found large regional differences in prices and trading volumes. Song et al. (2018) examined the Shanghai pilot ETS to investigate the transmission channels and interactions that shape carbon pricing. Lin and Jia (2019) used a CGE model to analyze the underlying pricing mechanisms and found a significant positive relationship between ETS prices and emission reductions. Wang et al. (2020) analyzed carbon price data from seven regional ETS pilots and provided useful insights for creating a more stable carbon pricing system. These studies revealed the complexity and significance of carbon pricing in China's ETS, highlighting the need for clearer and more stable price signals to support effective emissions control. In the area of price forecasting, Han et al. (2019) proposed a hybrid of combination-mixed data sampling regression model and back propagation neural network to perform real-time forecasting of weekly carbon prices in Shenzhen. Lu et al. (2020) applied six machine learning models to forecast daily carbon prices and trading volumes across eight pilot carbon markets in China.

2.2 Firm-Level Impacts of ETS

Scholars around the world have explored the firm-level impacts of ETS from multiple dimensions. ETS may impose additional costs on regulated firms, potentially influencing their output, profitability, innovation, or competitiveness. At the same time, it may also stimulate efficiency improvements, accelerate green innovation, or restructure resource allocation through market-based incentives.

Studies have shown varied firm-level responses to ETS policies, especially across different national and institutional contexts in Europe. Petrick and Wagner (2014) found no evidence that emissions trading lowered employment, gross output, or exports of manufacturing firms in Germany. Marin et al. (2018) also found that the EU ETS did not harm economic performance and instead, firms passed costs to customers and improved labor productivity. Joltreau and Sommerfeld (2019) found that the EU ETS had little to no effect on firms' competitiveness or profitability, although it had a small but positive impact on innovation. Klemetsen et al. (2020) examined that the EU ETS had a positive impact on both the environmental and economic performance of Norwegian manufacturing plants during the second phase.

In China, where the ETS is still at an early stage of development, empirical findings are similarly mixed. Xiao et al. (2021) found that ETS significantly improved the firm-level total factor productivity in China's pilot regions. Pan et al. (2022) also found that higher carbon market efficiency enhances the moderating effect of ETS on firms' total factor productivity in China. Zhao et al. (2022) examined listed companies in Shanghai and Shenzhen and found no significant green innovation effects from the ETS pilot at the industry-wide level and across the entire manufacturing sector, though notable improvements were observed among some resource-intensive industrial firms. Similarly, Yu et al. (2022) found that China's ETS pilot policy promoted green innovation among regulated firms, particularly in state-owned enterprises, firms located in the eastern region, and those with fewer financing constraints. The effect extends downstream through supply chain linkages while reducing innovation upstream, mainly through price mechanisms.

Previous studies present diverse findings, reflecting variations in research scope, methodological approaches, and institutional environments. These empirical results suggest that firm-level effects of ETS are highly context-dependent, shaped by institutional design, firm characteristics, and market dynamics. Further research is needed to better understand how policy design and market maturity interact with firm heterogeneity to influence these outcomes.

2.3 Carbon Leakage under Climate Policy

Carbon leakage is a central issue in academic and policy debates on the effectiveness of climate policy. It refers to the risk that emissions-constrained firms may relocate operations or shift production to regions with weaker environmental regulations. Numerous empirical studies have examined this issue, but the findings remain mixed. Martin et al. (2012) examined compensation mechanisms under the EU ETS and found that free allocation of permits to carbon-intensive and trade-exposed industries led to substantial overcompensation relative to actual carbon leakage risk. Borghesi et al. (2018) found that the EU ETS had a weak effect on the number of new overseas subsidiaries, but a stronger impact on production within existing ones. aus dem Moore et al. (2018) examined the impact of the EU ETS on firms' fixed asset holdings as an indicator of industrial relocation. They found no general evidence of deindustrialization, though the policy may have altered investment behavior among certain multinational enterprises. Naegelé and Zakla (2019) found no evidence that the EU ETS caused carbon leakage in European manufacturing. Verde (2020) also found no clear evidence of carbon leakage under the EU ETS, but noted that long-term effects remain underexplored. Caron et al. (2015) used a general equilibrium model to examine California's cap-and-trade program and found significant leakage effects. Sadayuki and Arimura (2021) found evidence of negative carbon leakage within firms under Japan's regional ETSs, as emissions fell at both regulated and unregulated facilities.

In China, carbon leakage has also gained academic attention. Yu et al. (2021) evaluated the impact of China's pilot ETS on OFDI and found that the regional ETS accelerated both the depth and breadth of China's OFDI, and that the Belt and Road Initiative further facilitated carbon leakage through investment. Alternatively, Du et al. (2022) employed a Staggered Difference-in-Difference model to examine the reverse investment leakage effect of China's regional ETS on unregulated, pollution-intensive firms. They found that the ETS significantly reduced the establishment of new subsidiaries by these firms in pilots. More recently, Huang et al. (2025) used data from 4,480 A-share listed companies and applied a two-way fixed effects difference-in-differences model under staggered treatment adoption. They found that the ETS promoted

investment relocation from pilot to non-pilot regions, contributing to the pollution haven literature.

Most existing studies on carbon leakage under China's carbon trading policies have been limited to the regional pilot ETS phase (2013 – 2017), examining whether emission constraints in pilot areas led to increased emissions or firm relocations in non-pilot regions. These works necessarily rely on data from before the national ETS launch in 2021 and therefore lack more recent data. They mainly focus on intra-national leakage and often overlook cross-border channels such as OFDI, which could represent a significant but underexplored mechanism for carbon leakage on an international scale.

This study helps fill this gap in the existing literature by focusing on a cross-border leakage pathway in the national ETS context. By explicitly examining the effects of the national market, this study allows for a more accurate and policy-relevant understanding at present. This study shifts attention to the international dimension by investigating firms' OFDI activities. It provides new empirical evidence on the global implications of China's climate policy and enriches the broader literature on carbon leakage under ETS in China.

3 Research Design and Methodology

3.1 Data

China announced the establishment of a national ETS in 2017, aiming to reduce carbon dioxide emissions through a market-based and cost-effective approach. However, the national carbon market did not officially begin trading until 2021. Consequently, this study treats the formal commencement of trading in 2021 as the policy intervention point and designates it as the treatment year in the empirical analysis. To effectively capture firms' behavioral responses over time, I construct a panel dataset covering the period from 2017 to 2023, including four years before the policy (2017–2020) and three years after (2021–2023). Consistent with Brunnermeier and Levinson (2004), using panel data allows for controlling unobserved firm-level heterogeneity. This time structure also facilitates the identification of the policy's dynamic effects and enhances the credibility of causal inference across the temporal dimension.

At the micro level, data are primarily obtained from the China Stock Market and Accounting Research (CSMAR) database and the annual reports of publicly listed firms. The dataset includes a range of indicators that capture firm-level characteristics, such as profitability, asset scale, production capacity, capital intensity, human capital, and R&D intensity. Furthermore, information on OFDI, including data on overseas subsidiaries, is incorporated to systematically reflect the scope and intensity of firms' internationalization.

In the process of sample identification, whether a firm is included in the national ETS is primarily determined based on official announcements issued by provincial-level governments. However, these announcements are typically made at the level of corporate entities rather than listed companies. A single listed company may operate multiple power plants across different regions, yet the announcements often specify only the names of individual plants without clearly indicating their affiliation with any listed parent company. This lack of explicit reference creates challenges for accurately classifying the sample. To address this issue, this study manually cross-checks the names of enterprises mentioned in the announcements with publicly available information on the operational structures of listed firms, and identifies 68 listed companies that

were first officially included in the national ETS in 2021. These firms constitute the treatment group in this study.

The control group is selected from listed companies in the same industries, primarily the electricity and chemical sectors, that are not yet included in the national ETS. These firms are identified from the CSMAR database using the China Listed Company Association's industry classification codes C26 (chemical manufacturing) and D44 (electric power production and supply), ensuring sectoral consistency with the treated group for matching. Propensity score matching (PSM) is conducted based on pre-policy covariates to ensure a high level of comparability between the treatment and control groups before the policy implementation. This matching strategy satisfies the balancing assumption and provides a methodological foundation for the identification of policy effects.

3.2 Propensity Score Matching

3.2.1 Theory and Implementation

PSM is a statistical technique used to transform observational data into quasi-experimental data, aiming to reduce bias arising from confounding variables and to strengthen the validity of the parallel trends assumption. The core idea is to achieve comparability between the treatment and control groups based on observed covariates, thus facilitating a more accurate estimation of policy or treatment effects. The method was first introduced by Rosenbaum and Rubin (1983). A key concept in PSM is the propensity score, which refers to the probability of an individual receiving the treatment given a set of covariates, mathematically expressed as:

$$e(X) = P(D = 1|X) \tag{1}$$

where D denotes the treatment status (1 = treated, 0 = untreated), and X denotes a vector of observable covariates. The propensity score serves as an effective balancing score. By matching individuals with similar propensity scores, the distribution of covariates between the treatment and control groups can be balanced, thereby achieving a quasi-random assignment effect in non-experimental settings.

The validity of PSM relies on the Conditional Independence Assumption (CIA) (Lechner, 2001), which states that, conditional on the observed covariates X , the treatment assignment is independent of the potential outcomes. That is: $(Y(0), Y(1)) \perp\!\!\!\perp D|X$, where $\perp\!\!\!\perp$ denotes statistical independence.

As a semi-parametric method, PSM depends on the correct specification of the propensity score model, which is estimated parametrically, while permitting non-parametric estimation of treatment effects. In this study, the probability of treatment assignment is estimated using a classical Logit model, specified as follows:

$$P(D = 1|X) = \frac{1}{1+\exp(-X\beta)} \quad (2)$$

where D denotes the treatment indicator, and X denotes the matrix of covariates. The Logit model characterizes the treatment assignment mechanism conditional on these covariates and serves as the foundation for subsequent matching procedures. Caliendo and Kopeinig (2008) systematically outlined the practical steps for implementing PSM, offering operational guidance for this empirical analysis.

In the research design, PSM is used as an identification strategy to control for firm-level heterogeneity prior to the implementation of the national ETS, thereby strengthening the credibility of the parallel trends assumption. Since firm characteristics may be influenced by the policy ex post, only pre-treatment covariates (specifically from the year 2020) are included in the matching model. This enhances comparability between treatment and control groups. The approach is consistent with that of Petrick and Wagner (2014), who based their matching procedure on pre-policy variables when assessing the effects of the EU ETS on German manufacturing firms.

For covariate selection, this study draws on the Ownership–Location–Internalization (OLI) paradigm from international business theory (Dunning & Lundan, 2008), with a focus on firm-specific advantages (FSAs) such as firm size, age, capital intensity, number of employees, and ROA. These variables capture a firm's resource endowment and organizational capabilities, which are closely linked to its motivation and capacity to respond to policy shocks. Given the study's focus

on firm-level behavioral responses, country-specific advantages (CSAs) are not included. To mitigate the influence of outliers and improve the distributional properties of the data, selected covariates are log-transformed.

In the matching procedure, nearest neighbor matching is used to pair treated units with control units that have the most similar propensity scores. Specifically, each treated unit is matched to four nearest neighbors from the control group based on the absolute distance in propensity scores. This 1-to-4 matching ratio aims to enhance statistical efficiency by incorporating more information from the control group, while maintaining a high degree of comparability between matched units. To further improve match quality and avoid poor matches, a caliper is applied to restrict the maximum allowable difference in propensity scores between matched units. Following the classical recommendation of Rosenbaum and Rubin (1983), the caliper is set to 0.2 times the standard deviation of the estimated propensity scores. In this study, the standard deviation is 0.1936, yielding a caliper width of approximately 0.04. This setting helps ensure accurate matching, adequate sample size, and mitigates the risk of inflated estimation variance or failed matches.

3.2.2 Matching Quality Evaluation

The core objective of PSM is to achieve covariate balance between the treatment and control groups. After completing the matching procedure, this study evaluates the quality of matching from multiple dimensions to determine whether the covariates are significantly more balanced.

At the model level, the pre-matching Logit model yields a McFadden pseudo R^2 of 0.2649, indicating that covariates strongly predict treatment assignment. The likelihood ratio test statistic is 83.01, suggesting significant differences in covariate distributions between groups. After matching, the pseudo R^2 drops sharply to 0.0115, and the test statistic falls to 4.74. These results indicate that the systematic relationship between covariates and treatment status has been substantially reduced, thereby improving covariate balance and strengthening the comparability between the treatment and control groups.

At the covariate level, the results presented in Table 1 indicate that systematic differences between the treatment and control groups have been substantially reduced through the

matching procedure. The unmatched sample reveals considerable imbalances across a wide range of covariates. For example, standardized mean differences (SMDs) exceed 100 percent for key variables such as total assets and employment, reflecting significant disparities in firm characteristics. Other variables, including capital intensity, debt ratio, and R&D investment, also exhibit substantial biases. These differences are statistically significant in nearly all cases, as confirmed by the corresponding t-tests, indicating that the two groups were initially not comparable on observable attributes. After matching, the distribution of covariates between the treatment and control groups becomes substantially more balanced. All SMDs fall below the conventional threshold of 25 percent, and several variables, including ROA, R&D investment, and employment, show differences of less than 10 percent, indicating minimal residual imbalance. Post-matching t-tests are no longer statistically significant, suggesting that systematic differences in covariate distributions have been largely eliminated. In addition, most covariates exhibit bias reduction rates above 80 percent, reflecting a notable improvement in overall covariate alignment. The visual evidence in Figure 1 further supports these patterns, confirming that the matching process effectively removed observable biases and provides a solid foundation for subsequent causal inference.

Figure 2 shows the kernel density distributions of propensity scores for the treatment and control groups before and after matching. Before matching (Panel a), the distributions differ markedly. The treatment group shows a wider and right-skewed distribution, while the control group is concentrated around lower propensity scores. After matching (Panel b), the distributions align closely. This near-complete overlap across the entire range of propensity scores indicates that the matching procedure has effectively addressed the initial imbalance.

Although minor residual differences remain, they are likely due to limited sample size and do not affect the validity of the analysis. The PSM procedure based on a Logit model achieves good covariate balance and provides a solid basis for estimating policy effects. The control group consists of non-covered firms that showed no significant differences from treated firms in the pre-treatment period. As a result, the final matched sample includes 68 treated firms and 97 control firms, forming a panel dataset with 1130 observations.

Table 1. Balance test results.

Matching Variable	Matched	Mean		Bias (%)	Bias Reduction (%)	t-stat	P-value
		Treated	Control				
Age	Unmatched	3.152	3.039	44.5	62.2	3.410	0.001
	Matched	3.133	3.169	16.8		1.450	0.148
ROA	Unmatched	0.033	0.039	8.3	97.0	0.630	0.533
	Matched	0.029	0.029	0.2		0.020	0.983
Debt ratio	Unmatched	0.497	0.389	52.0	78.6	3.780	0.000
	Matched	0.478	0.455	11.1		0.960	0.337
Total assets	Unmatched	23.961	22.186	131.8	91.1	8.780	0.000
	Matched	23.278	23.144	11.7		1.010	0.315
Employment	Unmatched	8.683	7.295	118.8	98.3	7.640	0.000
	Matched	8.099	8.080	2.1		0.180	0.859
R&D	Unmatched	18.205	17.520	37.2	99.8	2.360	0.021
	Matched	17.656	17.655	0.1		0.010	0.996
Capital intensity	Unmatched	14.218	13.468	70.2	81.4	4.940	0.000
	Matched	14.040	13.888	13.0		1.120	0.262

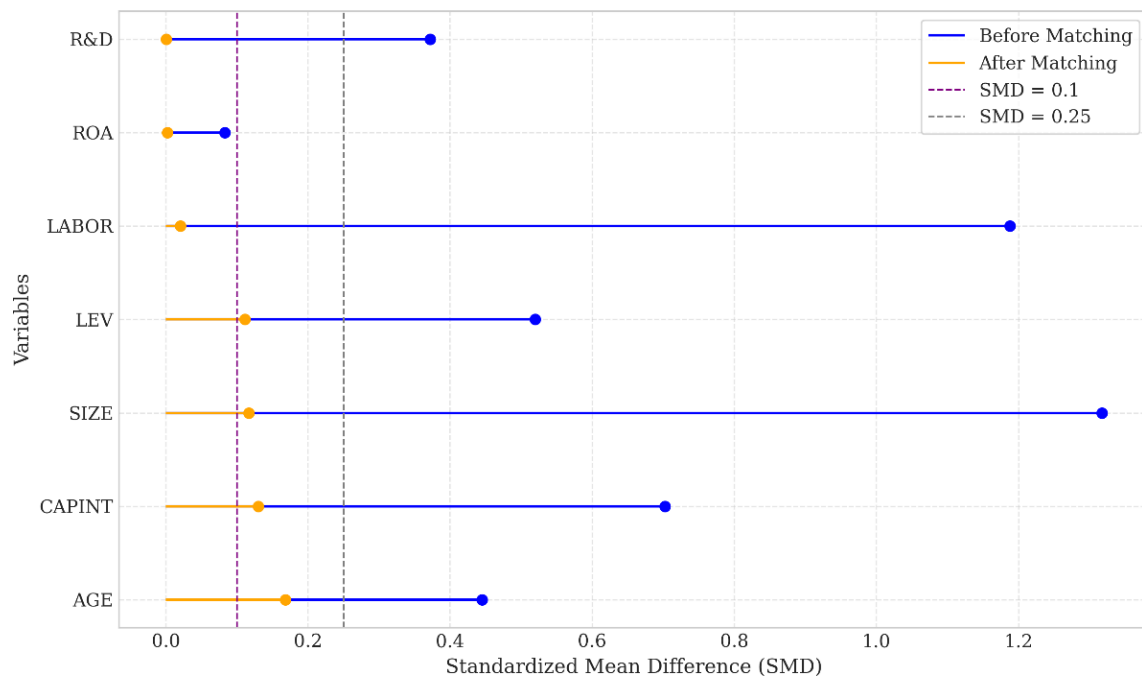


Figure 1. Standardized Mean Differences of Covariates Before and After Matching.

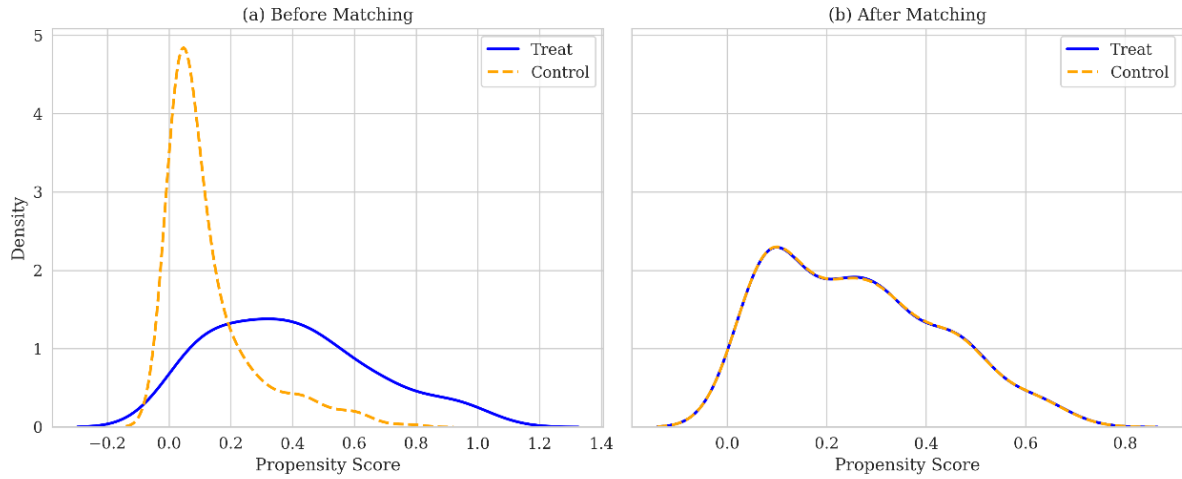


Figure 2. Kernel Density of Propensity Scores Before and After Matching.

3.2.3 Baseline Model

To study the impact of China's national ETS on firms' OFDI activities, this study adopts a Difference-in-Differences (DiD) approach. The DiD method identifies the net effect of the policy by comparing the differences in changes over time in OFDI behavior between the two groups, before and after the introduction of the national ETS. The baseline DiD model is specified as follows:

$$OFDI_{i,t} = \alpha_0 + \alpha_1 post_t + \alpha_2 ETS_i \times post_t + \mu_i + C_{i,t} + \varepsilon_{i,t} \quad (3)$$

Regarding the dependent variables, due to the difficulty in obtaining accurate data on firms' actual outward investment amounts, this study follows Yu et al. (2021) to measure OFDI behavior from two dimensions. The first is OFDI depth, which is proxied by the logarithm of the number of overseas subsidiaries a firm holds each year, reflecting the overall scale of its international operations. The second is OFDI breadth, measured by the logarithm of the number of countries or regions in which the firm has established subsidiaries, capturing the geographical scope of its overseas presence. Given that some firms may have zero overseas subsidiaries, resulting in zero values for both indicators, the transformation $\log(1 + x)$ is applied. This allows for the inclusion of all observations without distortion, preserving data completeness while maintaining interpretability on the log scale. These two proxies together provide a more comprehensive view of firms' investment relocation and allow for the examination of structural changes in OFDI.

Accordingly, in Equation (3), $OFDI_{i,t}$ denotes either the depth or the breadth of OFDI, and the model is estimated separately for each outcome.

The key explanatory variables in this study include ETS_i , $post_t$, and their interaction term $ETS_i \times post_t$, which together serve as the core of the DiD estimation. The variable ETS_i is a treatment indicator that equals 1 if a firm is covered by the national ETS, and 0 otherwise. The variable $post_t$ is a time dummy, taking the value of 1 for the years following the ETS implementation, and 0 for the pre-policy period. The interaction term $ETS_i \times post_t$ is the DiD estimator, identifying the average treatment effect of the national ETS on firms' OFDI by comparing changes over time between treatment and control groups. If the coefficient on the interaction term is significantly positive, it means that ETS-covered firms increased their OFDI more than non-covered firms after the ETS was introduced. This would suggest carbon leakage, where firms shift investment abroad to avoid domestic environmental costs. Conversely, if the coefficient is significantly negative, it indicates that the ETS reduced OFDI among regulated firms. In this case, the ETS may have helped contain outbound carbon-intensive investment rather than causing leakage. This specification enables the isolation of the policy's net impact, controlling for both time-invariant differences between firms and common time trends.

As for $C_{i,t}$, it represents a set of control variables. The model includes key firm-level characteristics that are closely related to internationalization decisions, such as firm age, ROA, leverage, R&D investment, capital intensity, and Tobin's Q. These variables capture FSAs that may influence a firm's capacity and motivation to expand internationally. Several of these variables are also used in the PSM process, ensuring consistency between the matching procedure and the subsequent regression analysis. Detailed definitions of all variables are provided in Table 2.

Entity fixed effects, denoted by μ_i , are also included to absorb all firm-specific characteristics that do not vary over time, such as industry affiliation or ownership structure. This controls for unobserved, time-invariant heterogeneity that may influence OFDI behavior. $\varepsilon_{i,t}$ is a random disturbance item in the model.

Table 3 shows the descriptive statistics of the relevant variables. On average, firms in the control group exhibit slightly higher levels of OFDI activity, with an OFDI depth of 0.894 and

breadth of 0.728, compared to 0.787 and 0.651, respectively, for the treatment group. ROA is winsorized, consistent with the PSM specification. A small number of leverage values exceeding 1 are due to firms undergoing restructuring that year. These observations are retained as they reflect real financial conditions. In addition, Tobin's Q and the intangible asset ratio have fewer observations due to missing data in firms' financial disclosures.

Based on the specification above, the empirical estimation is conducted using entity fixed effects regression, implemented via the Fixed Effects Ordinary Least Squares (OLS) method. Robust standard errors clustered at the firm level are employed to account for potential autocorrelation and heteroskedasticity, while firm-level fixed effects help control for unobserved, time-invariant heterogeneity across entities.

Table 2. Variable definition.

Category	Variable	Description
Dependent variables	OFDI depth	Log of the number of overseas subsidiaries
	OFDI breadth	Log of the number of countries/regions with firm subsidiaries
Explanatory variables	ETS	Treatment dummy: 1 if the firm is covered by the national ETS, 0 otherwise
	post	Post-policy dummy: 1 for years after ETS implementation (year 2021), 0 otherwise
	ETS×post	Interaction term: ETS policy effect (DiD estimator)
Control variables	Age	Log of firm age (in years)
	ROA	Return on assets, winsorized at the 1st and 99th percentiles
	Lev	Debt-to-asset ratio: total liabilities divided by total assets
	Size	Log of total assets
	R&D	Log of R&D expenditure
	CI	Log of capital intensity: fixed assets divided by number of employees
	TobinQ	Tobin's Q: market value divided by asset replacement value
	IAR	Intangible assets ratio: intangible assets divided by total assets

Note: All log-transformed variables are calculated using $\ln(1 + x)$ to account for zero values.

Table 3. Descriptive statistics.

Variable name	Treatment group (ETS covered)					Control group (ETS non-covered)				
	Obs.	Mean	S.D.	Min	Max	Obs.	Mean	S.D.	Min	Max
OFDI depth	450	0.787	0.989	0	3.714	679	0.894	0.978	0	3.638
OFDI breadth	450	0.651	0.793	0	2.944	679	0.728	0.723	0	2.996
Age	450	3.17	0.211	2.303	3.584	662	3.157	0.252	2.398	4.304
ROA	450	0.037	0.064	-0.25	0.208	661	0.041	0.066	-0.25	0.208
Lev	450	0.491	0.2	0.051	1.093	661	0.445	0.209	0.051	2.29
Size	450	23.833	1.594	19.413	28.337	661	23.003	1.248	20.058	27.072
R&D	450	14.194	8.003	0	23.36	679	14.904	6.969	0	20.932
CI	450	14.201	1.3	0	16.763	679	13.371	2.536	0	17.941
TobinQ	319	0.788	0.519	0.118	2.962	496	1.351	1.391	0.098	9.843
IAR	323	0.046	0.032	0.001	0.217	502	0.049	0.058	0.001	0.5

4 Empirical Results

4.1 Baseline Regression

Table 4 presents the results of the baseline DiD estimation based on the specification in Equation (3). Columns (1) and (2) report the estimated effects on OFDI depth and breadth, respectively.

The key variable of interest is the interaction term $ETS_i \times post_t$, which capture the average treatment effect of the ETS policy on covered firms relative to non-covered firms in the post-policy period. The results suggest that the national ETS had a significantly negative effect on firms' OFDI activities. Compared to non-covered firms, those included in the ETS reduced their number of overseas subsidiaries by approximately 10.84%, and the number of regions in which they operate by about 11.28%. These findings indicate a clear contraction in both the scale and geographic reach of international operations among regulated firms. In the fixed-effects specifications, the main effect of the ETS_i treatment indicator is absorbed due to its time-invariant nature and therefore does not appear in the model setting and regression results. This does not compromise the identification strategy, as the treatment effect is captured by the interaction term $ETS_i \times post_t$, which remains both interpretable and statistically meaningful.

The implementation of China's national ETS has had a negative impact on the OFDI activities of listed firms. This result differs from the typical expectation of carbon leakage, which suggests that tighter environmental regulations and climate policies may lead firms to move carbon-intensive production to countries or areas with lower carbon costs in order to avoid compliance pressure (Aichele & Felbermayr, 2012). However, this study finds no such evidence in the case of China. Firms covered by the national ETS have not expanded their international footprint but have instead scaled back their outward investment efforts, as reflected in both the number of foreign subsidiaries and the geographical spread.

This result contrasts with existing evidence from studies on the EU ETS. For example, aus dem Moore et al. (2019), in their study of German firms, found that ETS-covered companies were more likely to expand their foreign operations as a strategic response to regulatory pressure. Instead

of reducing capacity or retreating from international markets, these firms shifted assets abroad to offset rising domestic carbon costs. This pattern is often interpreted as a typical pathway of carbon leakage. Similarly, Borghesi et al. (2020) found that the impact of the EU ETS on outward investment by Italian manufacturing firms exhibited phased and heterogeneous effects. In the initial phase of the policy (Phase I), firms showed limited signs of relocation. However, as the system entered Phase II and firms adapted to the regulatory environment, those operating in more competitive sectors increasingly expanded into non-ETS countries. These findings suggest that the international effects of ETS policies are not uniform, but are influenced by industry-level exposure and the pace of institutional adjustment.

In China, the national ETS is still in the early stages of development. Key institutional elements such as market design, carbon pricing, and firms' adaptive capacity are not yet sufficient to induce significant carbon leakage. As shown in Figure 3, China's carbon price has remained at a low level over time, significantly below that of more mature markets such as the EU and the UK. It is far from reaching the level that would meaningfully influence firms' marginal investment decisions. Unlike large multinational corporations in the EU, most ETS-covered firms in China do not have mature carbon management systems. The existing cost accounting system in China does not have cost accounting for carbon emission indicators (Hu et al., 2022), making it difficult for firms to quantify and manage carbon-related expenses effectively. Moreover, the current carbon allowances are distributed for free, using benchmarking. This significantly weakens the cost signal of carbon pricing. Many firms have yet to internalize carbon costs and therefore face weak incentives to shift production overseas in response to regulation. Lacking the capacity to use carbon financial instruments or manage emissions portfolios effectively, firms tend to adopt a risk-averse approach rather than pursue new foreign investments. Furthermore, since China's ETS is still evolving from pilot programs to a fully institutionalized national system, ongoing uncertainty about policy continuity, allocation rules, and enforcement mechanisms reinforces cautious investment behavior and discourages investment relocation and cross-border expansion.

Additionally, the ETS has a stronger and more significant impact on the breadth rather than the depth of OFDI, suggesting that firms are more discouraged from entering new markets than from expanding in those where they already operate. This asymmetry reflects a typical path-

dependent pattern: under regulatory uncertainty, higher entry barriers, and increased transaction costs, firms tend to focus on strengthening existing international operations rather than exploring unfamiliar locations (Johanson & Vahlne, 1977). Existing subsidiaries offer greater institutional clarity, cultural understanding, and operational efficiency, which help reduce external risks. This pattern contributes to the stronger restraining effect of the national ETS on the geographic expansion of firms.

China's national ETS has not induced substantial carbon leakage as reported in some international studies. Instead, it appears to have limited investment relocation in the short term. Empirical evidence indicates that the ETS has significantly constrained corporate international expansion strategies. These findings highlight the broader implications of climate policy for global capital flows and the internationalization pathways of firms.

Table 4. Baseline regression results.

Variables	(1) OFDI depth			(2) OFDI breadth		
	Parameter		T-stat	Parameter		T-stat
post	-0.0873	*	-1.9297	-0.0571		-1.5284
ETS×post	-0.1084	**	-2.475	-0.1128	***	-3.1171
Age	0.7903	***	2.7449	0.7414	***	3.1175
ROA	0.0525		0.1735	0.2313		0.9254
Lev	0.3908	***	3.0372	0.4322	***	4.0665
Size	0.2744	***	6.2002	0.1527	***	4.177
R&D	0.0031		1.3503	0.0008		0.4188
CI	-0.0156		-0.4558	-0.0124		-0.4377
TobinQ	0.0592	***	3.0989	0.0165		1.0458
IAR	2.8205	***	4.2315	0.155		0.2816
const	-7.9468	***	-7.0296	-5.0147	***	-5.3705
Obs	815			815		
R ² (Within)	0.3842			0.3377		

*Notes: Asterisks denote significance levels: *** Statistical significance at 1% level, ** at 5% level, and * at 10% level.*

T-statistics are based on clustered standard errors.

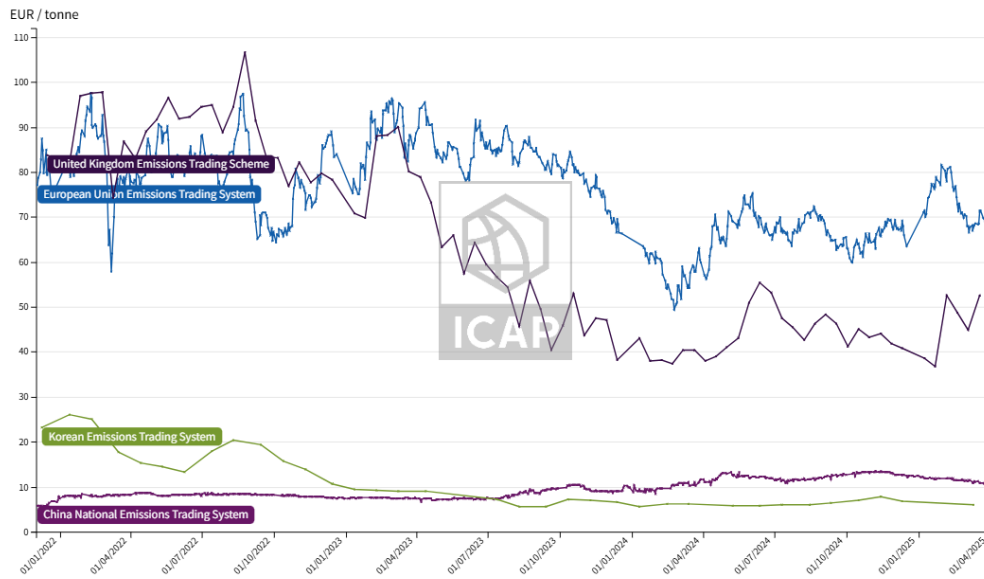


Figure 3. Comparative Trends in Carbon Allowance Prices across ETS Markets (2021–2025), Source: International Carbon Action Partnership.

In addition to the policy effect, several firm-level characteristics are closely associated with OFDI behavior. The estimated coefficients for several control variables align with economic expectations. Increases in firm size, age, and profitability are positively associated with both the depth and breadth of OFDI, suggesting that firms' internal improvements in financial strength and organizational experience support internationalization. As firms grow older, they benefit from accumulated institutional knowledge and managerial capacity, which help facilitate overseas operations. Similarly, higher returns on assets reflect stronger internal financing capacity, enabling firms to pursue international opportunities while managing potential risks. A rising debt ratio is also positively linked to OFDI activity, partly indicating that greater access to external finance can support expansion abroad even under regulatory pressure. Internal capabilities play a vital role in shaping firms' responses to globalization and in formulating their internationalization strategies, especially under conditions of policy and market uncertainty.

Tobin's Q is positively and significantly associated with OFDI depth, but shows no significant effect on OFDI breadth. When a firm's Tobin's Q increases, signaling stronger growth expectations, its overseas expansion is more likely to focus on regions where it already operates, rather than entering entirely new markets. This behavior suggests a tendency to deepen existing OFDI

pathways, where returns are more predictable and operational risks are lower. Similarly, as the share of intangible assets rises, such as proprietary technology or brand value, firms tend to reinforce current overseas operations instead of expanding into unfamiliar regions with higher institutional or cultural uncertainty. This pattern suggests risk aversion and a preference for path-dependent expansion.

In contrast, capital intensity and R&D investment are not significantly associated with OFDI in this study, suggesting that production structure and innovation input are not the main drivers of Chinese firms' international expansion under the ETS. While these factors do not appear to drive OFDI under the current ETS framework, they may still suggest relevance in alternative green policy settings where innovation and production transformation are more directly incentivized.

4.2 Robustness Check

4.2.1 Placebo Test

A placebo test is a widely used falsification method in empirical research to assess the validity of the parallel trends assumption in DiD models. It is based on counterfactual reasoning: if the observed treatment effect is truly caused by the policy, then assigning a false policy implementation year and re-estimating the model should yield no significant results. This method helps identify whether the estimated effect is confounded by pre-treatment trends, anticipation effects, or selection bias. An insignificant result under the placebo setting confirms the reliability of the parallel trends assumption of the DiD framework, thereby enhancing the internal validity of the model and supporting a more credible causal interpretation. From a theoretical perspective, the placebo test is part of a broader falsification strategy aimed at ruling out alternative explanations and strengthening the identification strategy. As noted by Bertrand et al. (2004), it also helps address concerns related to serial correlation and inflated statistical significance in DiD estimates. This is particularly important in studies with a limited number of treated units or short panel durations, where the risk of model misspecification or baseline group differences is more pronounced. In such cases, the placebo test functions as a very critical robustness check.

To ensure the credibility of the identification strategy in the baseline model, this study conducts a placebo test by assuming 2019 as a false policy year, two years before the actual launch of the national ETS, and re-estimates the baseline DiD model. The specification remains identical to the main model, except that the post-treatment period is redefined to begin in 2019. The purpose of this setting is to verify that the estimated policy effect observed in the post-2021 period is not driven by unobserved trends, reverse causality, or other time-varying shocks unrelated to the national ETS. If the ETS policy only took effect from 2021, then no significant treatment effect should be observed under the placebo setting. Conversely, a significant result would suggest possible violations of the parallel trends assumption or the presence of omitted confounders. If the ETS policy indeed had a causal effect starting in 2021, then no statistically significant treatment effect should be detected when using a pseudo-policy year. In contrast, a significant coefficient in the placebo test would indicate potential violations of the parallel trends assumption or the presence of omitted confounders.

Table 5 presents the regression results from the placebo test. The study also emphasizes the key interaction term $ETS_i \times post_t$, which captures any spurious treatment effects before the actual implementation of the policy. The estimated effects are near zero, and the results indicate no statistically significant impact of the treatment on either OFDI depth or breadth. These findings indicate that the treatment and control groups followed similar OFDI trends before the ETS was implemented, thereby supporting the validity of the parallel trends assumption underlying the DiD design. It strengthens the main empirical findings by indicating that the estimated policy effects are unlikely to be driven by pre-existing trends or unobserved anticipation effects.

The coefficients of other firm-level controls are largely aligned with theoretical expectations and previous findings. Firm size continues to be a strong and highly significant predictor of OFDI in both dimensions, confirming that as firms grow over time, they tend to expand their international operations due to their greater resource base and organizational capacity. Tobin's Q also shows a strong positive link with OFDI, especially investment depth, indicating that firms are more likely to invest abroad when growth prospects improve. Moreover, Financial leverage is positively related to both OFDI depth and breadth in the placebo model. These patterns provide further support that internal capabilities play a critical role in shaping OFDI behavior over time.

The placebo test confirms the robustness of the DiD framework. The absence of significant effects under a false policy implementation year suggests that the treatment effect identified in the main analysis is unlikely to be driven by pre-existing trends or spurious correlations. It confirms the ETS's causal impact on firms' OFDI activities.

Table 5. Placebo Test regression results.

Variables	(1) OFDI depth			(2) OFDI breadth		
	Parameter		T-stat	Parameter		T-stat
post	0.046		0.9452	0.0502		1.1905
ETS×post	-0.0013		-0.0283	-0.0082		-0.2115
Age	-0.202		-0.3733	-0.3177		-0.6775
ROA	-0.1131		-0.3079	-0.0259		-0.0815
Lev	0.2929	**	2.0705	0.3203	***	2.6115
Size	0.4447	***	7.5115	0.3271	***	6.3738
R&D	0.0042	*	1.7734	0.0029		1.4174
CI	-0.0031		-0.0721	-0.0204		-0.5543
TobinQ	0.0622	***	2.7129	0.0387	*	1.9461
IAR	4.9884	***	3.6092	1.7333		1.4466
const	-9.1288	***	-4.953	-5.7977	***	-3.6286
Obs	815			815		
R2 (Within)	0.3213			0.2427		

*Notes: Asterisks denote significance levels: *** Statistical significance at 1% level, ** at 5% level, and * at 10% level. T-statistics are based on clustered standard errors.*

4.2.2 Event Study Analysis

To further validate the parallel trends assumption of DiD and capture the dynamic changes in firms' OFDI behavior before and after the implementation of policy, this study adopts an event study as an extended empirical strategy. The event study method is widely used to evaluate the impact of policy shocks or external events on economic behavior or market responses. Its core logic is based on dividing time into multiple periods relative to the event and dynamically estimating the evolution of treatment effects. This method enables a more detailed examination of policy impact over time, going beyond average treatment effects to investigate when and how the effects emerge.

Originally developed in financial economics to assess the influence of discrete events on stock prices (MacKinlay, 1997), the event study has been widely applied in public policy evaluation, labor economics, and environmental studies. From a methodological perspective, the event study can be viewed as an extension of the DiD design. It introduces a series of relative time dummies, each indicating the number of years before or after the policy year, which are then interacted with the treatment group indicator. This enables the model to estimate time-varying treatment effects and construct a dynamic treatment path. A key advantage of this method is its ability to test the parallel trends assumption more formally. If the interaction terms for pre-policy periods are statistically insignificant, it suggests that the treatment and control groups followed similar paths before the intervention, thereby supporting the DiD approach. Moreover, the event study provides insight into the timing and persistence of policy effects, revealing whether the impact is immediate, delayed, or gradually intensifying. It also allows researchers to detect potential anticipation effects or underlying adjustment mechanisms, such as institutional inertia or strategic behavior. By capturing the temporal structure of the policy impact, the event study enhances the empirical credibility of the analysis and contributes to a deeper understanding of how firms respond to the climate policy over time.

In this study, the event study approach is not only employed to examine whether the national ETS has a causal impact on Chinese firms' OFDI, but also to visually track the dynamic pattern of policy effects over time and assess whether their timing aligns with the actual implementation logic.

As in the baseline model introduced earlier, the standard DiD framework relies on a two-period, two-group design, comparing treatment and control groups before and after the policy to estimate the average treatment effect. In contrast, the event study approach introduces the concept of event year in equation (4), which expands the time dimension into multiple relative years to capture the dynamic evolution of treatment effects.

$$event\ year_{i,t} = t - T_{policy} \quad (4)$$

A series of dummy variables is constructed to represent each year relative to the policy implementation date. In this study, the policy implementation year 2021 is set as the reference

point. These variables are interacted with the treatment indicator to estimate year-specific treatment effects, denoted as TE_k . Formally, the treatment effect variable is defined as:

$$TE_k = ETS_i \times \mathbb{1}(\text{event year}_{i,t} = k) \quad (5)$$

In this specification, ETS_i is a treatment group indicator variable, equal to 1 if firm is covered in the ETS, and 0 otherwise. $\mathbb{1}(\cdot)$ denotes an indicator function that equals 1 if the observation falls in a given relative year, and 0 otherwise. To avoid multicollinearity, one relative time dummy is omitted from the regression specification. As standard, this baseline omitted case is the one period prior to policy implementation ($k=-1$ in equation (5)) which serves as the baseline group (Clarke and Tapia-Schythe, 2021).

Based on the construction of year-specific treatment indicators, the corresponding event study model is formulated as follows to estimate dynamic treatment effects over time:

$$OFDI_{i,t} = \alpha_0 + \sum_{k \neq -1} \delta_k \cdot (ETS_i \times \mathbb{1}(\text{event year}_{i,t} = k)) + \mu_i + C_{i,t} + \varepsilon_{i,t} \quad (6)$$

where δ_k represents the treatment effect in the k -th year relative to the policy implementation and all estimated coefficients capture deviations from the pre-policy period immediately preceding the implementation.

The regression results for this model are presented in Table 6, with the corresponding visual representations shown in Figures 4 and 5. The model specification remains consistent with the original DiD regression, using OFDI depth and breadth as dependent variables, respectively. Columns (1) and (2) report the estimated coefficients, t-statistics, and significance levels. Figure 4 displays the event study results for OFDI depth, while Figure 5 does so for OFDI breadth, visually depicting the relative treatment effects over the years.

The estimation results for OFDI depth show that in the two years before policy implementation, treatment effects are nearly zero and statistically insignificant, which confirms the validity of the parallel trends assumption. From 2021, the interaction terms turn significantly negative, suggesting that the ETS implementation may have reduced firms' incentives to expand their overseas subsidiaries. This negative effect becomes more pronounced in the following year, indicating a sustained and lagged policy impact. The OFDI breadth results reveal a similar trend.

Before the policy intervention, no systematic differences in trends are observed between the treatment and control groups, further supporting the model's identification strategy. From the year of policy implementation, the estimated coefficients shift from zero to negative, and the direction remains consistent. These findings indicate that, despite rising carbon costs and regulatory uncertainty, Chinese firms hesitate to enter new markets to avoid domestic carbon constraints. This lack of expansion suggests no clear evidence of carbon leakage.

The event study extends the baseline DiD analysis by introducing a temporal perspective that static models do not capture. Beyond its role in validating robustness, it captures the gradual evolution of firms' responses to the national ETS, offering additional insight into the dynamics of investment adjustment over time.

Table 6. Event Study Regression Results for Parallel Trends Test.

Variables	(1) OFDI depth			(2) OFDI breadth		
	Parameter		T-stat	Parameter		T-stat
TE: Year -3	-0.0286		-0.493	-0.0079		-0.1654
TE: Year -2	0.0127		0.222	0.0202		0.4276
TE: Year 0 (Policy)	-0.1533	***	-2.6831	-0.1257	***	-2.6639
TE: Year +1	-0.1033	*	-1.743	-0.1217	**	-2.4857
TE: Year +2	-0.1781	***	-2.9116	-0.1491	***	-2.9516
Age	0.385	*	1.8516	0.4901	***	2.8536
ROA	-0.041		-0.136	0.1699		0.6818
Lev	0.365	***	2.8241	0.4161	***	3.8976
Size	0.2706	***	6.0867	0.1504	***	4.0954
R&D	0.0046	*	1.9153	0.0015		0.7684
CI	-0.019		-0.5542	-0.0146		-0.5158
TobinQ	0.0567	***	2.9573	0.0147		0.9288
IAR	2.7153	***	4.0706	0.0758		0.1376
const	-6.5599	***	-7.1083	-4.1531	***	-5.4488

*Notes: Asterisks denote significance levels: *** Statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.*

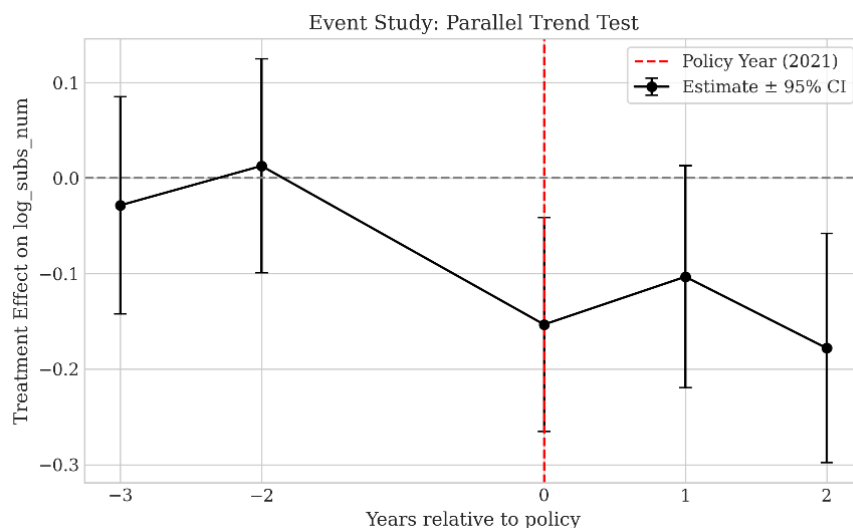


Figure 4. Event Study: Impact of ETS on OFDI Depth.

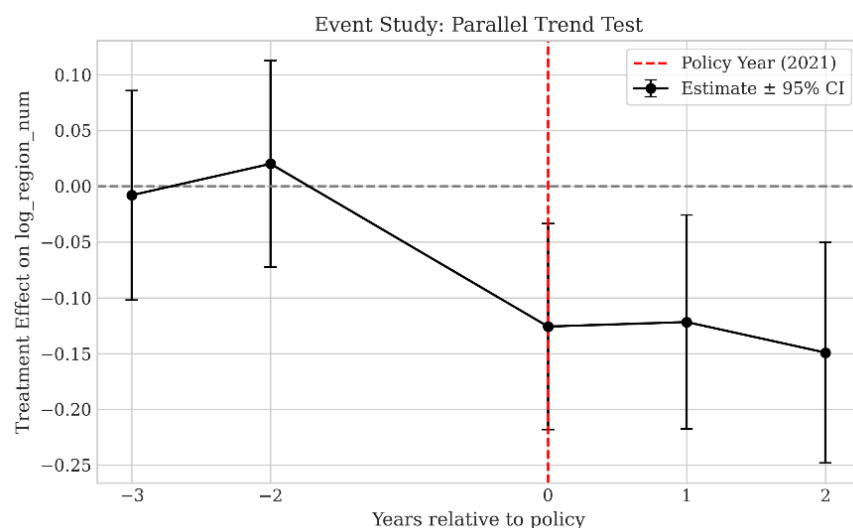


Figure 5. Event Study: Impact of ETS on OFDI Breadth.

4.3 Heterogeneity

The Belt and Road Initiative (BRI) serves as China's primary platform for international cooperation and economic engagement (Nedopil, 2024). Given its strategic importance, the BRI offers a valuable perspective for assessing whether firms adjust their responses to environmental regulation when investing in regions that enjoy closer institutional alignment and policy support from China. Incorporating the BRI dimension into the analysis allows for an evaluation of whether national-level initiatives can shape or moderate the influence of climate policies such as the national ETS on firms' outward investment behaviors. While the conventional DiD framework

captures the average effect of the national ETS on OFDI, it may fail to account for variations in firms' responses across different geographic regions. To explore destination-specific heterogeneity, a triple-difference (DDD) model is employed based on whether firms' overseas subsidiaries are located in BRI countries. The DDD model extends the DiD framework by introducing a third dimension of interaction, allowing for the analysis of heterogeneous treatment effects across national strategic context. The estimation model is specified as follows:

$$OFDI_{i,t} = \alpha + \beta_1 post_t + \beta_2 BRI_i + \beta_3 \cdot (ETS_i \times post_t) + \beta_4 \cdot (ETS_i \times BRI_i \times post_t) + \mu_i + C_{i,t} + \varepsilon_{i,t} \quad (7)$$

where $OFDI_{i,t}$ denotes the OFDI performance measured by the logarithm of the number of its overseas subsidiaries. Specifically, a binary variable is constructed to indicate whether a firm has subsidiaries located in BRI countries. This variable is interacted with the ETS treatment status and the post-policy period to generate the triple interaction term. As a result, the coefficient β_4 on this term is the key parameter of interest, capturing the differential effect of the ETS policy on BRI-related investment. The model includes entity fixed effects μ_i to absorb time-invariant unobserved heterogeneity at the firm level. A set of time-varying firm-level controls $C_{i,t}$ is also included to enhance the robustness of the estimation results. Regression results of this DDD model are showed in Table 7.

The results indicate that while the climate policy imposes an overall constraint on OFDI expansion, the negative effect is notably weaker for investments related to BRI countries. Specifically, the positive and statistically significant coefficient on the triple interaction term suggests that treated firms exhibit greater resilience in their BRI-related OFDI activities following the policy implementation, compared with their investments in non-BRI regions and with the performance of untreated firms. This finding may reflect the supportive role of national strategic initiatives in encouraging OFDI along the BRI, which could partially offset the restrictive effects of environmental regulations.

China's BRI promotes the development of large markets through mutual cooperation focused on energy and infrastructure (Sun et al., 2020). The joint development of the BRI has significantly improved trade and infrastructure conditions in participating countries, reducing institutional and

logistical barriers to investment (Zhang & Zhang, 2018). These improvements create more favorable conditions for Chinese firms to expand internationally, especially in sectors such as energy, construction, and manufacturing. Consequently, the BRI plays a critical role in facilitating China's OFDI by reducing entry costs and increasing the strategic value of overseas markets. For example, investment projects in BRI countries often benefit from a broad range of supportive policies, such as subsidized green loan interest rates, reduced corporate income tax, and the establishment of green credit guarantee mechanisms. These forms of support help significantly alleviate financial pressure and institutional frictions faced by firms during overseas expansion (Chin et al., 2024). Moreover, BRI countries tend to enjoy higher levels of policy coordination and project prioritization under the bilateral economic cooperation frameworks established with China, making it easier for firms to obtain support from both governments and financial institutions.

At the same time, the BRI reflects China's broader national strategy to enhance regional connectivity, upgrade infrastructure, and promote international capacity cooperation. Its strategic orientation increases the likelihood that overseas investments aligned with the initiative will receive institutional support and preferential access to key resources. Furthermore, the growing availability of green financial instruments such as green bonds and green credit, along with the establishment of multilateral and bilateral cooperation mechanisms between China and BRI countries, has further supported green economic development in the region (Zhang et al., 2021). These initiatives help reduce financing barriers and institutional constraints for firms operating abroad by improving access to capital, strengthening project evaluation standards, and enhancing risk-sharing arrangements. Consequently, while the ETS raises overall compliance costs for companies, the institutional support and green financing available through the BRI framework can help mitigate these pressures and strengthen the resilience of Chinese firms' investments abroad.

The DDD model results highlight the role of investment destination as a key moderating factor in determining firms' responses to climate policy. National strategies like the BRI may help mitigate the negative effects of environmental regulation on OFDI, contributing to a more sustainable path of globalization within the framework of the green transition.

Table 7. DDD Model Regression Results

Variables	Parameter		T-stat
post	-0.0865	**	-2.2482
BRI	0.5421	***	14.965
ETS×post	-0.1099	**	-2.4464
ETS×post×BRI	0.1599	***	2.7009
Age	0.5273	**	2.1385
ROA	-0.0136		-0.053
Lev	0.1744		1.5843
Size	0.2516	***	6.6939
R&D	0.0022		1.1124
CI	0.0088		0.3043
TobinQ	0.0603	***	3.7193
IAR	3.6639	***	6.448
const	-7.0837	***	-7.3453
Obs	815		
R ² (Within)	0.414		

Notes: Asterisks denote significance levels: *** Statistical significance at 1% level, ** at 5% level, and * at 10% level. T-statistics are based on clustered standard errors.

5 Conclusion

This study examines how China's national ETS, introduced in 2021, has affected firms' OFDI. The main analysis adopts a two-step empirical method. First, propensity score matching is applied using pre-treatment firm characteristics to construct a comparable control group. Then, a difference-in-differences model is applied to the matched sample to estimate the policy's effect. The model measures OFDI from two dimensions: the number of overseas subsidiaries, which reflects the scale of international operations, and the number of countries or regions where these subsidiaries are located, which reflects the geographic structure of internationalization. This study finds no evidence that the national ETS in China has led to carbon leakage at the firm level.

The empirical findings indicate that firms covered by the ETS, compared with non-covered firms, significantly reduce both the scale and the geographic scope of their overseas investment following the implementation of the policy. This contraction is reflected in a lower number of foreign subsidiaries and host regions. The results are robust to a placebo test using a fictitious policy year and are further supported by an event study that captures the dynamic adjustment process. These patterns suggest that, rather than relocating emission-intensive operations and corporate investment abroad to avoid domestic carbon costs, regulated firms tend to scale back their international activities. This conservative adjustment is likely driven by regulatory uncertainty and the relatively weak carbon price signal during the early stages of the ETS. Such behavior suggests that many firms, particularly those without well-developed carbon management capabilities, prioritize short-term operational stability over long-term global growth when confronted with a new and evolving regulatory framework.

The heterogeneity analysis further finds that the negative impact of the ETS on OFDI is significantly weaker for investments in BRI countries for the treatment group. This suggests that OFDI activities in these regions show greater resilience, potentially due to the institutional support available under the BRI framework. Firms operating in BRI countries may benefit from enhanced policy coordination, financial instruments and diplomatic support, all of which help lower investment risks and ease the compliance burden associated with domestic climate policy. These

findings highlight the potential complementarity between national development strategies and climate regulation in shaping the direction of firms' international investment behavior.

Together, the findings offer three key policy implications.

First, China's national ETS maintains its environmental integrity, which provides a positive signal regarding the effectiveness of China's carbon market. Despite low carbon prices and the prevalence of free allowance allocation in the early stages of the ETS, regulated firms do not shift emission-intensive activities abroad. However, their primary response is to scale back outward investment rather than pursue low-carbon transformation. This conservative adjustment may help prevent leakage in the short term, but it could also constrain the green upgrading of international operations. Relying solely on cost-based constraints may therefore be insufficient to drive substantive structural change, and future policy design should aim to balance risk management with incentives for green transition.

Second, the design of the ETS should aim to strike a balance between environmental goals and firms' global competitiveness. In the short term, regulatory uncertainty and underdeveloped institutional arrangements may discourage international expansion, particularly in industries with limited flexibility or international operating experience. Enhancing the transparency, predictability, and long-term stability of the carbon pricing mechanism is therefore essential. A gradual shift from free allowance allocation to auction-based systems, combined with clearly defined rules for quota distribution and robust carbon accounting frameworks, can help firms internalize carbon costs and adopt forward-looking strategies in response to climate regulation.

Third, green OFDI should be promoted as a policy priority. Under frameworks such as the BRI, institutional and financial support for sustainable investment can help firms align their internationalization with climate goals. Given rising carbon costs at home, firms may increasingly look to green investments abroad not just as a compliance strategy but as a competitive advantage. Expanding access to green finance, including credit support and bond issuance, and fostering international cooperation on environmental standards can facilitate this transition. Integrating the ETS with wider industrial and trade policies can help transform carbon constraints into drivers of sustainable international growth.

Despite the contributions of this study, several limitations remain, pointing to directions for future research. First, due to the recent implementation of the national ETS, available data are limited to the first two to three years after the policy came into effect. The analysis focuses on short-term effects. As the carbon market matures and carbon prices rise, firms' responses may evolve over time. Future studies could extend the time frame to assess whether the observed contraction persists or gives way to green restructuring and renewed international expansion. Second, the sample is restricted to listed firms, and the measurement of OFDI relies only on publicly available subsidiary registration data, which may not fully capture the scale, type, or strategic intent of firms' foreign investment. Moreover, the behavior of non-listed enterprises, particularly small and medium-sized firms, with different financial and governance structures, may differ significantly. Expanding data sources and sample coverage would enhance the overall applicability of the findings and allow for a more detailed analysis of firm-level heterogeneity. Third, while this study measures OFDI in terms of overall scale and geographic reach, it does not distinguish between investment types. Future research could investigate whether firms reduce high-carbon activities while increasing their involvement in low-carbon sectors, thereby offering more precise insights into the composition of OFDI and the structural impact of climate policy.

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