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JEL Classification L25, L60, O13, Q53, Q58, R11

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Evidence of Firm-level Pollution Leakage resulting from Clean Air Policy in China

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1. Introduction

Pollution leakage caused by uneven environmental regulations is commonly explained by the Pollution Haven Hypothesis (Birdsall and Wheeler, 1993, Mani and Wheeler, 1998), which posits that differences in regulatory stringency drive polluting activities from regions with stricter controls to those with more lenient rules (Jaffe et al., 1995). In this context, firms facing higher compliance costs may engage in regulatory arbitrage by shifting pollution-intensive operations to affiliates in less-regulated regions (Gibson, 2019; Bartram et al., 2022). While most studies focus on cross-border pollution leakage, less attention has been paid to within-country leakage (Chung, 2014; Cai et al., 2016a; Li and Zhou, 2017; Misch and Wingender, 2024), especially in large economies with substantial regional disparities, such as China (Lin and Zhang, 2023; Li et al., 2024; Huang et al., 2025) and the United States (Bartram et al., 2022).

The first theoretical studies of cross-border leakage applied to climate change used computable general equilibrium (CGE) frameworks (Babiker, 2005; Burniaux and Martins, 2012). Babiker (2005) finds leakage rates from 25% to 130% depending upon differing assumptions. Studies of other pollutants often rely on industry-aggregate or regional-aggregate data, which obscure firm-level heterogeneity and produce mixed results. For example, Cai et al. (2016a) found that stricter environmental regulations deter foreign direct investment, while Shao et al. (2019) found no significant effects. Recent studies have adopted firm-level approaches to examine how firms reallocate emissions or pursue pollution offshoring strategies (Sadayuki and Arimura, 2021; Bartram et al., 2022; Dechezleprêtre et al., 2022; Chen et al., 2025).

However, full relocation of production is rare due to high adjustment costs. Instead, large firms often outsource pollution-intensive activities to subsidiaries in less-regulated areas to minimize compliance costs (Gibson, 2019; Bartram et al., 2022; Chen et al., 2025). Recognizing this, several studies compared production or emissions shifts between regulated firms and their less-regulated affiliates (Li and Zhou, 2017; Gibson, 2019; Moore et al., 2019; Bartram et al., 2022; Chen et al., 2025). Nevertheless, identifying firm-level leakage remains challenging due to complex organizational structures and limited emissions data, particularly in developing countries (Zhang and Zhao, 2023).

To support higher output in less-regulated areas, firms often invest in subsidiaries where environmental controls are weaker, enabling more subtle forms of pollution relocation (Bartram et al., 2022; Gibson, 2019). Although some studies examine cross-border (Saussay and Sato, 2024; Carril-Caccia and Baleix, 2024) and domestic investments patterns (Du et al., 2025; Huang et al., 2025), many rely on simplified proxies, such as mergers and acquisitions (M&A) (Saussay and Sato, 2024; Carril-Caccia and Baleix, 2024) or subsidiary counts (Du et al., 2025; Huang et al., 2025). These approaches overlook more complex investment behavior such as the expansion of existing facilities or intra-firm reallocation of resources.

This issue is particularly relevant in developing countries like China, where firm-level emissions data is often incomplete. A deeper understanding of investment behavior can improve analyses of pollution leakage from an investment perspective. To address this gap, we manually collected investment data from annual reports of 390 listed pollution-intensive firms. This dataset allows us to assess whether regulated firms increase investment in production-linked subsidiaries located in less-regulated areas in response to environmental regulations. We focus on pollution-intensive industries due to their high emissions and sensitivity to environmental policies. Additionally, listed firms typically operate multiple production-related subsidiaries in less-regulated regions, providing greater flexibility to shift investment. Furthermore, annual reports offer detailed subsidiary-level information, including names, investment amounts, and locations, enabling a more precise identification of pollution leakage. This approach improves accuracy and facilitates an in-depth exploration of the spatial and temporal dynamics of pollution leakage and its underlying mechanisms.

We examine pollution leakage in the context of China's 2013 *Air Pollution Prevention and Control Action Plan* (hereafter the "Clean Air Policy"), the country's most stringent environmental regulation targeting air quality improvement in recent years (Cheng et al., 2023). This policy provides an ideal empirical setting for several reasons. First, it mandates strict emission standards, compelling polluting firms to quickly adopt cleaner technologies or shut down operations, with the goal of improving air quality by 2017. Second, it imposes stricter standards in certain key areas, made up of 47 major cities across the "Three Regions and Ten City Clusters"[1], creating clear regional disparities. This regional differentiation allows for a Difference-in-Differences (DID) approach to be adopted to evaluate the policy's effects on pollution leakage. Our findings confirm that the policy led to significant pollution leakage through investment shifts. Regulated firms significantly increased investments in production-related subsidiaries located in outside the 47 regulated key cities compared to less-regulated firms after the policy.

This paper contributes to several strands of literature. First, we refine the measurement of pollution leakage by focusing on investment flows to production-related subsidiaries rather than simply counting the number of subsidiaries. Existing studies relying on subsidiary counts may overlook the scale of expansionary investments, potentially underestimating the true impact of environmental regulations. In so doing, our approach provides a more precise assessment of pollution leakage. Second, the extensive investment data we collected enables a detailed spatiotemporal analysis. Our findings provide insight into the specific interprovincial shifts in pollution driven by the Clean Air Policy, revealing that pollution leakage is not

[1] The "Three Regions" refer to the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Pearl River Delta, while the "Ten City Clusters" refer to ten key city clusters located along major air pollution transmission corridors.

confined to neighboring provinces but also involves long-distance transfers to western regions. Furthermore, we examine the characteristics of recipient cities and firms that may moderate the pollution leakage induced by the policy. Our results indicate that industrial agglomeration, transportation infrastructure, and subsidiary networks in recipient cities facilitate pollution relocation, while firms' innovation capabilities help mitigate pollution leakage. Finally, we provide a fuller picture of the Clean Air Policy by examining its unintended consequences. While prior research has emphasized its benefits for air quality (Liu et al., 2021; Yu et al., 2022), public health (Yao et al., 2022), and innovation (Cheng et al., 2023), our findings reveal a significant shift of pollution-intensive investments from eastern regions to western regions. This underscores the need to account for pollution leakage when evaluating the long-term effectiveness of environmental policies.

The remainder of this paper is organized as follows: Section 2 provides historical background on the policy's implementation. Section 3 outlines the empirical design and data of the study, while Section 4 presents the main findings of the Clean Air Policy's impact on pollution leakage. Section 5 discusses the spatiotemporal patterns and moderating factors, and Section 6 concludes.

2. Policy Background

Since the 1990s, China's rapid economic growth and heavy reliance on fossil fuels has led to severe air pollution, with many cities frequently experiencing heavy haze (Li et al., 2021). Growing public concern over health impacts prompted the government to implement a series of national air pollution control plans (Li et al., 2019). The first national clean air plan introduced in 2013 targeted critical pollution issues, followed by the 2018–2020 plan that broadened regulatory efforts and the 2023 plan that emphasized long-term sustainable improvements in air quality.

Our study focuses on the first national clean air plan. In September 2013, the State Council issued the Clean Air Policy, a landmark initiative aimed at improving air quality (OECD, 2016). It is widely regarded as China's most stringent air pollution regulation (Li et al., 2019; Cheng et al., 2023). The policy introduced a comprehensive strategy, which included imposing capacity controls in energy-intensive and high-polluting industries, shutting down small coal plants, and enforcing stricter vehicle emission standards, demonstrating the government's strong commitment to tackling pollution.

Although national in scope, the Clean Air Policy imposed stricter regulations in specific areas, including tougher industry entry requirements, more stringent emission reduction mandates, and enhanced pollution control measures. The more highly regulated areas involved

47 cities divided between the Three Regions and the Ten City Clusters, as illustrated in Figure 1[2]. These regions, characterized by high economic activity, dense populations and severe air pollution, were subject to stricter regulations. This differential treatment likely incentivized firms to shift pollution-intensive activities away to less regulated areas, contributing to pollution leakage.

The region-specific policy enables a DID approach to assess its impact on pollution leakage. Previous studies have employed DID methods to evaluate the Clean Air Policy and have demonstrated its suitability (Li et al., 2019; Yu et al., 2022; Cheng et al., 2023; Zhou et al., 2024). By comparing changes in outcomes between treatment and control groups before and after the policy's implementation, we can isolate its effects on pollution leakage.

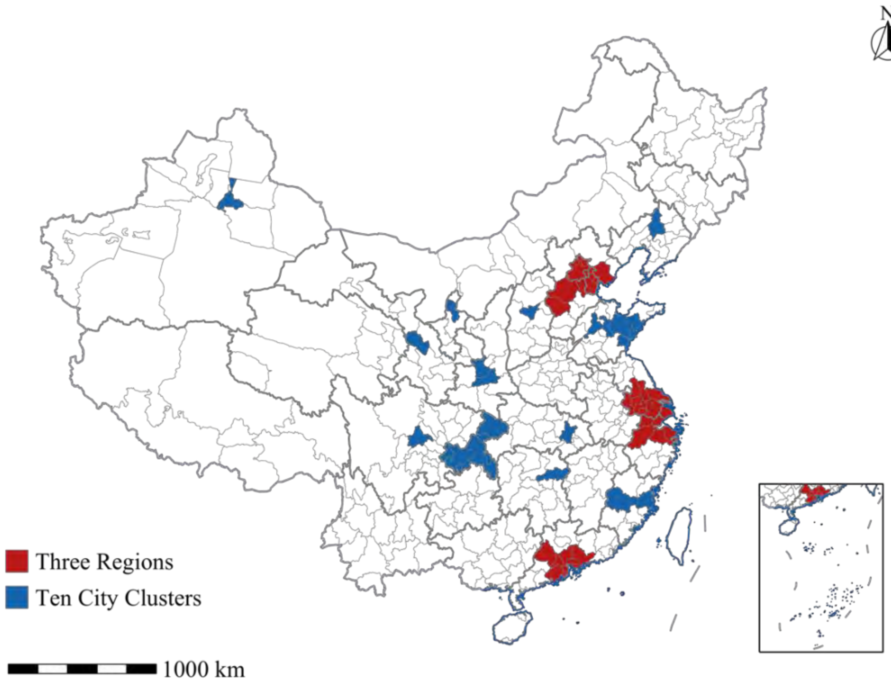


Figure 1. Key regulated areas for the Clean Air Policy

3. Empirical design

3.1 Specifications

This section outlines our empirical approach to examining how the Clean Air Policy contributes to pollution leakage. We employ a DID approach to compare changes in investment between treatment and control groups before and after the policy's implementation. The baseline estimation is represented as follows:

[2] Figure 1 plots the distribution of the 47 cities mandated by the Clean Air Policy, with 29 cities in the Three Regions and 18 cities in the Ten City Clusters. Each cluster consists of cities within one or multiple provinces, but since some are geographically separated, the map shows 12 distinct city clusters.

$$Y_{it} = \beta_0 + \beta_1 policy_{it} + (\boldsymbol{s}_c \otimes \boldsymbol{f}(\boldsymbol{t}))' \boldsymbol{\psi} + \lambda_i + \mu_t + \delta_{zt} + \theta_{pt} + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes pollution leakage outcomes for pollution-intensive firms i in year t; $policy_{it}$ is an indicator variable equal to one if firm i is located in a key regulated area and year t is post-policy; otherwise, it equals zero. Since the policy was introduced in September 2013, we assume its effects began in 2014.

A primary concern in DID estimation is the non-random assignment of treatment, which may reflect pre-existing regional characteristics and introduce bias. To address this, we control for a set of pre-treatment city-level characteristic variables $\boldsymbol{s}_c$ that may have influenced the selection of key areas to be regulated. To capture their dynamic effects over time, we incorporate three alternative specifications for $\boldsymbol{f}(\boldsymbol{t})$: (1) interacting $\boldsymbol{s}_c$ with a third-order polynomial function of time to impose a structured trend, (2) interacting $\boldsymbol{s}_c$ with an indicator for the year after the policy's implementation, $post_t$, to allow their effects to shift after policy implementation, and (3) interacting $\boldsymbol{s}_c$ with year fixed effects to fully capture their time-varying influence. We also include firm fixed effects λ_i to control for time-invariant firm characteristics and year fixed effects μ_t to account for common time shocks. To further reduce potential confounding, we incorporate industry-year fixed effects δ_{zt} and province-year fixed effects θ_{pt} to control for industry- and region-specific environmental policies that may evolve differently over time (Wu et al., 2023; Kwon et al., 2023). Here, z represents 2-digit National Economic Industrial Classification (NEIC) industries, and p represents province. Standard errors ε_{it} are clustered at the city level to account for within-city correlation.

3.2 Variable definition

3.2.1 Dependent variables

To examine pollution leakage, we focus on investment shifts from regulated firms to subsidiaries in less-regulated areas. Since pollution-intensive industries are most affected by the Clean Air Policy, we build our sample drawn from firms in pollution-intensive industries, as defined by the *Program for the First National Pollution Source Census* in 2007[3], to ensure more accurate identification of the policy's impact. We then restrict the sample to firms that existed continuously over 2010 to 2017, yielding 411 firms (223 treated and 188 controls). Finally, we applied propensity score matching to improve comparability between groups,

[3] *Program for the First National Pollution Source Census* specified 11 pollution-intensive industries, which are: Papermaking and Paper Products Industry (C22); Agricultural and Sideline Food Processing Industry (C13); Chemical Raw Materials and Chemical Products Manufacturing Industry (C26); Textile Industry (C17); Ferrous Metal Smelting and Rolling Processing Industry (C31); Food Manufacturing Industry (C14); Electricity/Heat Production and Supply Industry (D44); Leather, Fur, Feathers (Down), and Their Products Industry (C19); Petroleum Processing, Coking, and Nuclear Fuel Processing Industry (C25); Non-metallic Mineral Products Industry (C30); Non-ferrous Metal Smelting and Rolling Processing Industry (C32).

resulting in the 390 firms used in our baseline regressions presented in Section 4.1 (see also Appendix Table A1).

We identify pollution leakage using subsidiary-level investment data from the annual reports of listed firms, which include subsidiary names, locations, industries, and cumulative year-end investments. We manually extracted this data using Python and supplemented missing industry or location details with information from Qichacha, a comprehensive database of registered firms (Lin and Zhang, 2023). Subsidiaries were classified based on their 2-digit industry codes from the *National Economic Industrial Classification (2011)*.

However, not all subsidiary investments indicate pollution leakage. Two conditions must be met. First, subsidiaries must be located outside the 47 most heavily regulated cities. Second, subsidiaries must have production linkages with their parent firms, as only such subsidiaries can absorb polluting activities (Bartram et al., 2022)[4]. We identify production-linked subsidiaries as those sharing the same 2-digit industry as their parent firms[5]. Applying these criteria, each observation represents the cumulative pollution-related investment of a parent firm into one of its subsidiaries by year-end. We aggregated this data at the parent-firm and year levels to calculate annual pollution investment. For robustness, we consider two alternative dependent variables: per-unit investment (normalized by 2010 total assets) and the number of production-linked subsidiaries.

3.2.2 Independent variables

Our independent variable of interest is $policy_{it}$. If the coefficient β_1 is significantly greater than 0, it indicates that the Clean Air Policy has led firms in key areas to increase investment in production-related subsidiaries in less-regulated areas, relative to their counterparts in the 47 key cities.

3.2.3 Pre-treatment variables

Our control variables consist of pre-treatment city-level characteristics. Following Li et al. (2016), identifying these characteristics allows us to control for differential outcome trends between more regulated and less regulated areas that may arise from factors related to the Clean Air Policy. The policy identifies key areas based on economic development, air pollution levels, and population density. Accordingly, we include variables in three categories. First, economic

[4] To improve identification, we focus on production-linked subsidiaries in pollution-intensive sectors. While this reduces misclassification, some leakage may still go undetected. Future research could benefit from more detailed firm-level emissions data.

[5] Due to widespread diversification among listed firms in China, 4-digit industry codes may not fully capture the scope of pollution-intensive activities. Many such firms operate across multiple 4-digit codes within the same 2-digit category. Using 4-digit codes may therefore underestimate pollution transfer. We define production-related subsidiaries as those sharing the same 2-digit industry code with the parent firm. While this improves coverage, we acknowledge that variation in pollution intensity within 2-digit categories may still be overlooked.

indicators include GDP per capita, fiscal revenue, fiscal expenditure, and secondary industry output[6]. Second, pollution indicators include annual average concentrations of SO_2, O_3, NO_x, $PM_{2.5}$ and PM_{10}. Third, we use pollution per square kilometer as a proxy for population density. All variables are measured in 2010. Economic and population density data are sourced from the *China City Statistical Yearbook*, while air pollution data come from the China High Air Pollutants dataset, which provides remote sensing data at hourly intervals, aggregated into annual averages at the regional level.

3.3 Data preprocessing and summary

Before estimation, outcome variables were winsorized at the 1st and 99th percentile. To improve comparability between firms inside and outside the 47 key regulated areas, we estimate a probit model for treatment assignment using firm-level covariates and compute propensity scores. The sample is then restricted to firms within the region of common support, where propensity score distributions overlap across treatment and control groups. Appendix Table A1 presents the covariates and results of the balancing test, while Table 1 provides descriptive statistics.

Table 1. Descriptive Statistics

Variables	N	Mean	SD	Min	Max
Panel A: Dependent variables					
Investment	3120	6.883	22.620	0.000	211.196
Per-unit investment	3120	0.142	0.585	0.000	9.620
No. of subsidiaries	3120	3.094	7.583	0.000	136.000
Panel B: Pre-treatment characteristics at city level					
SO_2	3120	30.408	13.417	1.900	60.162
$PM_{2.5}$	3120	55.115	14.281	24.179	87.594
PM_{10}	3120	94.901	26.595	40.329	155.880
O_3	3120	86.376	6.777	67.983	100.888
NO_2	3120	34.530	9.021	9.760	50.532
(log) Population density	3120	6.319	0.768	2.890	7.840
(log) GDP per capita	3112	10.773	0.526	9.468	12.073
(log) Industry output	3120	17.560	1.120	14.277	19.523
(log) Fiscal revenue	3120	14.652	1.347	11.331	17.174
(log) Fiscal expenditure	3120	15.062	1.101	11.711	17.313
Panel C: Firm covariates					
ROA	3120	6.695	7.102	-34.985	71.787
Net profit margin	3120	6.687	15.107	-132.603	167.490
Debt-to-Asset ratio	3120	49.628	25.856	1.083	218.634
Equity ratio	3120	1.328	1.658	-6.797	10.125
Revenue growth rate	3120	29.112	39.555	-75.240	594.823
Tobin Q	3120	1.963	1.026	0.926	10.700
Fixed asset ratio	3120	0.356	0.188	0.004	0.902
Age	3120	13.641	4.106	5.000	32.000
(log) Employee	3120	7.653	1.256	3.296	11.592
(log) Total asset	3120	21.876	1.260	18.367	25.782

[6] Secondary industry output reflects regional economic development and the level of industrialization, accounting for the largest share of economic activity in many areas (Zhang et al., 2024).

4. Empirical results

4.1 Baseline results

Table 2 presents baseline results based on equation (1), using investment as the primary outcome. Column (1) presents estimates without pre-treatment controls; Columns (2)-(4) progressively incorporate pre-treatment variables with different time trend specifications. Across all specifications, the coefficients are consistently positive and significant, suggesting that the Clean Air Policy led pollution-intensive firms in key areas subject to regulation to increase investment in production-related subsidiaries in less-regulated areas. Columns (5) and (6) extend the analysis to our alternative dependent variables: per-unit investment and the number of subsidiaries. Both alternatives also show significant positive effects, reinforcing the main findings.[7]

Table 2. Effects of the Clean Air Policy on pollution leakage

	Investment				Per-unit investment	No. of subsidiaries	Parent's output
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
policy	2.4230***	2.117***	2.276**	2.276***	0.156**	1.624***	-0.293**
	(0.634)	(0.799)	(0.909)	(0.921)	(0.070)	(0.598)	(0.121)
Control * T		Yes					
Control * T^2		Yes					
Control * T^3		Yes					
Control * post			Yes				
Control * Year FE				Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3096	3096	3096	3096	3096	3096	2925
R-sq	0.946	0.946	0.946	0.946	0.656	0.357	0.893

Notes: ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are in parentheses. The number of observations in Column (7) are slightly lower due to missing parent firm output data.

Stricter regulations often prompt firms to reallocate production to less-regulated regions to reduce compliance costs, leading to pollution leakage (Bartram et al., 2022; Chen et al., 2025). To further validate this mechanism, we examine the Clean Air Policy's effect on parent firm output. A decline in output, coupled with increased pollution-related investment in subsidiaries, would indicate leakage from more regulated to less regulated areas. Following Chen et al. (2025), we measure parent firm output using the logarithm of revenue. Column (7)

[7] Since the number of subsidiaries is a count variable that does not fit a linear regression model as well as a continuous variable, R-squared for Column (6) is much lower.

shows that firms in key areas experienced a significant decline in output while increasing investment in production-related subsidiaries, reinforcing the evidence of pollution leakage.

4.2 Event study

The identifying assumption underlying the DID estimation is that, in the absence of the Clean Air Policy, investment trends in both more regulated and less regulated areas would have followed parallel trajectories. Therefore, we estimate an event-study model described by Braghieri et al. (2022) to test for parallel trends and study the dynamics of treatment effects:

$$Y_{it} = \alpha_0 + \sum_{k=-4}^{3} \gamma_k D_{i,t+k} + (\boldsymbol{s}_c \times \mu_t)'\boldsymbol{\psi} + \lambda_i + \mu_t + \delta_{zt} + \theta_{pt} + \varepsilon_{it} \qquad (2)$$

Where $D_{i,t+k}$ is a set of indicators equal to one if firm i is in the key areas and year t is k years away from policy implementation. The omitted category is k = -1. All other settings are consistent with Equation (1). Figure 2 presents the event-study results, which support the parallel trend assumption: coefficients for pre-policy years are close to zero and statistically insignificant. Importantly, no significant trends are observed before policy implementation, strengthening the validity of our DID approach. Figure 2 also provides insights into the dynamic effects of the policy. Following implementation, investment in production-related subsidiaries show a gradual upward trend, initially statistically insignificant, but becoming more pronounced in both magnitude and significance over time. This pattern suggests a delayed adjustment period as firms gradually responded to the policy, reallocating investments in the subsequent periods.

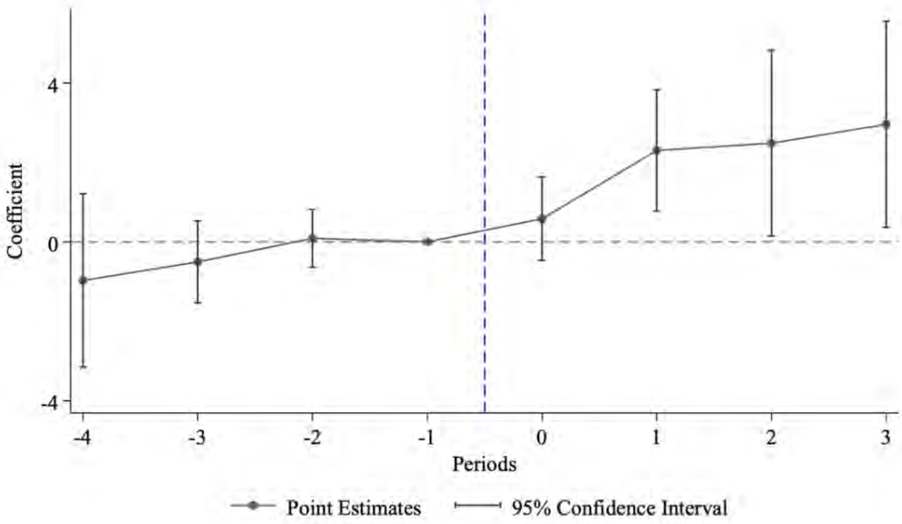


Figure 2. Event study results for pollution leakage

4.3 Spillover-robust DID

Theoretically, regulatory intensity is uniform across the less regulated areas, so pollution relocation between less-regulated areas is unlikely, ensuring the validity of the DID assumption. However, place-based policies may generate spillover effects if nearby control units are indirectly affected, which can bias estimates (Butts, 2021). For instance, firms in less-regulated areas adjacent to any of the 47 key regulated areas may anticipate future regulation expanding geographically and shift investment to more distant areas. To address this concern, we adopt a spillover-robust DID specification based on Butts (2021):

$$Y_{it} = \beta_0 + \beta_1 policy_{it} + \sum_{j=1}^{n}(1 - policy_{it})bin_{ij} + (\boldsymbol{s}_c \square \mu_t)'\boldsymbol{\psi} + \lambda_i + \mu_t + \delta_{zt} + \theta_{pt} + \varepsilon_{it} \tag{3}$$

where bin_{ij} is an indicator for firm i located within a specific geographic distance bin j. These indicators estimate the potential spillover effect on control firms over varying distance ranges, providing a clearer picture of how proximity to treatment units influences firms in less regulated areas. If the coefficients for bins are insignificant or become insignificant beyond a certain distance, our baseline results are not contaminated by spillover. We set the maximum spillover distance at 120 km as this corresponds to the median maximum distance between regulated and less-regulated firms. Following Cao and Chen (2022)[8], we define 20 km bins to balance the identification of spillover and estimation precision. All other model specifications remain consistent with Equation (1).

Table 3 presents the spillover-robust results. Column (1) replicates the baseline estimate from Column (4) of Table 2 for reference. Column (2) reports the adjusted policy effect, and Columns (3)–(8) account for potential spillover effects across different distance bins. The coefficient in Column (2) is smaller than in Column (1) but remains statistically significant. Among all distance bins, only the 40–60 km range shows a weakly significant spillover effect, suggesting limited spatial spillovers and confirming that the Clean Air Policy led to pollution leakage, even after accounting for spatial effects.

Table 3. Estimates of spillover-robust DID specification

	Diff-in-Diff	Diff-in-Diff with Spillover						
	Policy	Policy	Policy 0~20 km	Policy 20~40 km	Policy 40~60 km	Policy 60~80 km	Policy 80~100 km	Policy 100~120 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Invest-ment	2.276***	2.1511**	1.108	-0.058	-2.772*	-2.151	0.715	-0.280
	(0.921)	(1.074)	(1.599)	(0.939)	(1.425)	(2.176)	(2.755)	(1.747)

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are in parentheses. Column (1) replicates the estimate from Column (4) of Table 2. The remaining columns labeled "Diff-in-Diff with Spillovers" presents estimates from Equation (3).

8 Guo and Chen (2022) set the width of the bin to 25 km. In our case, if we were to set the width to 25 km, we would not be able to ensure that all distance bins are equal so to maintain uniformity across bins, we set the width of each distance bin to 20 km.

4.4 Robustness checks

4.4.1 Adjust the clusters of standard errors

In our preferred specification, standard errors are clustered at the city level to account for potential correlations among firms within the same city. We also cluster standard errors at the province level, capturing potential correlations among firms within the same province. Column (1) of Table 4 indicates that our baseline results remain robust after this adjustment.

Table 4. Additional robustness checks

	Adjust clusters	Rule out competitive policy	Rule out anticipation	
			1 year lead	2 year lead
	(1)	(2)	(3)	(4)
policy	2.276***	2.390**	0.713	1.048
	(0.736)	(0.921)	(0.695)	(0.770)
tour		-0.175		
		(1.075)		
pilot		-5.002**		
		(1.957)		
Control * Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry- Year FE	Yes	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes	Yes
N	3096	3096	1935	1935
R-sq	0.947	0.947	0.964	0.964

Notes: ∗, ∗∗, and ∗∗∗ indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are in the parentheses. *tour* equals one if the firm is in a city selected for interviews, and *pilot* equals one if the firm is in a pilot city under the Energy Conservation and Emission Reduction Fiscal Policies (ECERFP). Observations in Column (3) and (4) are smaller since we exclude post-policy years.

4.4.2 Rule out competitive policies

The central government has issued multiple policies to combat air pollution simultaneously, which may partially overlap with the Clean Air Policy and confound our results (Scott, 2024). In our sample period, there are two other significant air pollution policies that need to be considered. One is the so-called Environmental Protection Interview (EPI) policy issued by the Ministry of Environmental Protection in 2014, and the other is the pilot Comprehensive Demonstration Cities for Energy Conservation and Emission Reduction Fiscal Policies (ECERFP), which was jointly issued by the Ministry of Finance and the Ministry of National Development in 2011 (Sun and Feng, 2023).

The EPI is a regulatory measure to interview local governments and relevant departments that fail to fulfill their environmental protection duties. It aims to improve the environmental governance of local government by issuing warnings and recommendations (Sun et al., 2024). Previous studies have analyzed its impact on air pollution prevention (Wang et al., 2023; Pan et al., 2024). Since the policy specifically targets local governments failing to meet environmental regulations and pressures them to enforce stricter regulations, firms in EPI-targeted cities may have been required to reduce emissions, which could contribute to pollution leakage.

The ECERFP, implemented between 2011 and 2014, provided fiscal incentives to 30 pilot cities to promote cleaner production and energy efficiency (Fan and Liang, 2023). By encouraging firms to adopt cleaner technologies and improve energy efficiency, this policy may have influenced investment decisions, potentially mitigating pollution leakage.

To address the potential confounding effects of these concurrent policies, we follow Cao and Chen (2022) by incorporating two additional policy indicators into our preferred specification: one indicating whether a firm is located in an EPI-targeted city, and another for ECERFP pilot cities (Zhou and Lin, 2025). Column (2) of Table 5 demonstrate that the baseline estimates remain robust after controlling for these additional policies. This confirms that the observed effects are attributed to the Clean Air Policy rather than overlapping regulatory interventions.

4.4.3 Rule out anticipation effects

A potential concern is that firms may have anticipated the implementation of the Clean Air Policy and adjusted investment strategies in advance, leading to biased estimates. To mitigate this concern, we follow Cao and Chen (2022) and conduct an anticipation test by advancing the policy implementation year by one and two years, respectively, and generate corresponding false policy variables. We re-estimate Equation (1) using these pseudo-policy years. If coefficients are insignificant, it suggests no pre-treatment adjustments. The results in Columns (3) and (4) of Table 4 show that the false policy variables are statistically insignificant, ruling out anticipation effects.

4.4.4 Placebo test

To ensure that our baseline estimates are not driven by spurious correlations or omitted variables, we conduct a placebo test by randomly assigning regulated areas. Specifically, we generate a pseudo-treatment group, generate a false policy indicator, and repeat the DID estimation 1,000 times. Figure 3 shows that the distribution of placebo coefficients is centered around zero and remain substantially lower than our baseline estimate of 2.276. These findings confirm that our results are unlikely to be driven by unobservable factors, reinforcing the validity of our baseline estimates.

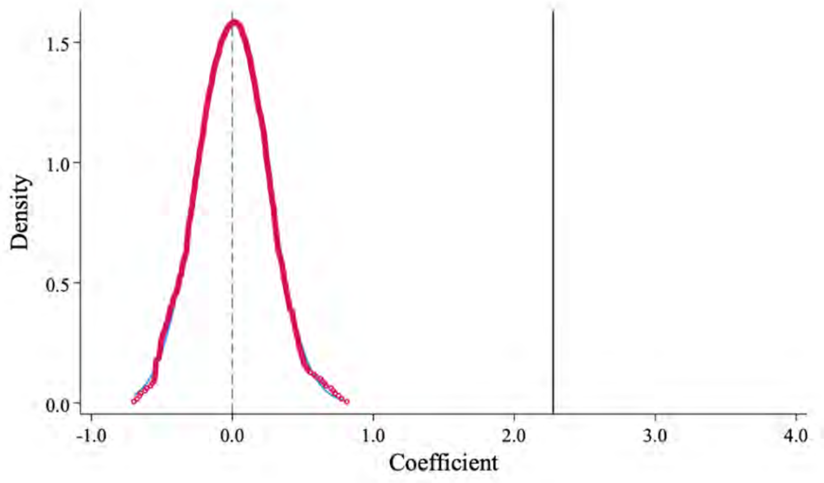


Figure 3. Placebo test

Notes: solid line represents the estimates of our preferred specification, which is 2.276.

4.4.5 City-pair panel

If pollution-intensive firms in highly regulated areas reallocate investment to less-regulated regions, we should observe a shift in pollution-related investments from regulated to less-regulated cities following the Clean Air Policy. To test this, we construct a city-pair panel dataset, where each observation represents the investment flow from a polluter city (the origin of pollution investment) to a receiver city (the destination of pollution investment). The specific model is as follows:

$$Y_{ijt} = \beta_0 + \beta_1 policy_{ijt} + (\boldsymbol{s_i} \square f(\boldsymbol{t}))' \boldsymbol{\psi} + \lambda_i + \mu_t + \phi_{ij} + \theta_{pt} + \delta_{jt} + \varepsilon_{ijt} \quad (4)$$

Where i represents the polluter city, j represents the receiver city, t represents the year, and p presents the province of the polluter city. Y_{ijt} represents the pollution investment flow from polluter city i to receiver city j in year t. $policy_{ijt}$ is an indicator variable equal to one if the polluter i is a city within the key areas, receiver j is a less-regulated city and year t is post-policy implementation. $\boldsymbol{s_i}$ are pre-treatment characteristics of the polluter city, as specified in equation (1), which are interacted with three different time trends specifications. λ_i are polluter city fixed effects, μ_t denotes year fixed effects, ϕ_{ij} are polluter-receiver city fixed effects, θ_{pt} are polluter province-by-year fixed effects, and δ_{jt} are receiver city-by-year fixed effects. Standard errors ε_{ijt} are clustered at the polluter city level. Columns (1) - (3) of Table 5 present the results from the city-pair panel model, with $\boldsymbol{s_i}$ interacted with three different time trends, consistent with the baseline regression. Our findings indicate that the Clean Air Policy significantly contributed to pollution leakage from regulated key areas to less regulated areas, reinforcing our baseline results. This suggests that pollution-intensive firms strategically increased investments in subsidiaries in less-regulated regions to mitigate regulatory costs.

Table 5. City-pair panel model

	(1)	(2)	(3)
	Investment	Investment	Investment
policy	8.157***	8.711***	8.711***
	(2.894)	(3.006)	(3.007)
Control * T	Yes		
Control * T^2	Yes		
Control * T^3	Yes		
Control * post		Yes	
Control * Year FE			Yes
Polluter FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Polluter-Recipient FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
Recipient-Year FE	Yes	Yes	Yes
N	155040	155040	155040
R-sq	0.851	0.851	0.852

Notes: Each observation indicates investment from polluter *i* to recipient city *j* in year *t*; *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are in the parentheses.

5. Further Discussion

5.1 Policy Heterogeneity

The regulatory intensity of the Clean Air Policy varies across regions, with stricter measures implemented in the Three Regions compared to the Ten City Clusters. This raises the question of whether the policy's impact differs between firms in these two regions. To explore this, we examine the heterogeneous effects of the policy by dividing the treatment group into two sub-treatment groups (similar to the approach taken by Buntaine et al. (2024)) – Three Regions treatment (T1) and Ten City Clusters treatment (T2) – and construct the following model:

$$Y_{it} = \beta_0 + \beta_1 policy_{it}^{regions} + \beta_2 policy_{it}^{clusters} + (\boldsymbol{s_c} \square \boldsymbol{f}(\boldsymbol{t}))' \boldsymbol{\psi} + \lambda_i + \mu_t + \delta_{zt} + \theta_{pt} + \varepsilon_{it} \quad (5)$$

where $policy_{it}^{regions}$ is an indicator variable equal to one if firm *i* is located in the Three Regions and year *t* is post-policy, while $policy_{it}^{clusters}$ equals one if firm *i* is in the Ten City Clusters during the same period. All other specifications remain consistent with Equation (1). The coefficients of interest, β_1 and β_2, capture the differential impacts of the Clean Air Policy on the two sub-treatment groups relative to the control group. Additionally, we report p-values from F-tests with the null hypothesis $\beta_1 = \beta_2$, testing whether the policy effect differs significantly between the Three Regions and the Ten City Clusters.

The results in Table 6 indicate that the estimated coefficient for firms in the Three Regions (β_1) appears larger in magnitude and more statistically significant than that for firms in the

Ten City Clusters (β_2). While the F-tests do not reject the null hypothesis that β_1 and β_2 are equal, the consistently higher magnitude and significance of β_1 suggest a stronger policy impact on firms in the Three Regions.

Table 6. Heterogeneous policy effects between Three Regions and Ten City Clusters

	(1)	(2)	(3)
	Investment	Investment	Investment
$policy^{regions}$	2.682**	2.940**	2.940**
	(1.211)	(1.402)	(1.420)
$policy^{clusters}$	1.898*	2.064*	2.064*
	(1.014)	(1.077)	(1.091)
H_0:T1 = T2	$p = 0.624$	$p = 0.607$	$p = 0.612$
Control * T	Yes		
Control * T^2	Yes		
Control * T^3	Yes		
Control * post		Yes	
Control * Year FE			Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry- Year FE	Yes	Yes	Yes
Province-Year FE	Yes	Yes	Yes
N	3096	3096	3096
R-sq	0.946	0.946	0.947

Notes: p indicates the probability of null hypothesis that $\beta_1 = \beta_2$. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are in the parentheses.

5.2 Spatial patterns of pollution leakage

Previous studies of pollution leakage suggest that firms tend to relocate emissions to nearby regions, with the intensity of leakage diminishing as distances increase. This phenomenon, often referred to as "pollute thy neighbor", underscores the localized nature of pollution spillovers (Helland and Whitford, 2003; Chen et al., 2018; Wei et al., 2019; Lu and Ouyang, 2024). While existing research has focused on whether pollution leakage primarily affects adjacent regions, few studies have systematically examined its broader spatial and temporal patterns (Wu et al., 2017). To examine spatial patterns of pollution leakage more precisely, we restructure the data at two levels: firm–recipient city–year and firm–distance–year, allowing us to analyze both provincial and distance-based trends.

5.2.1 Destinations for pollution leakage

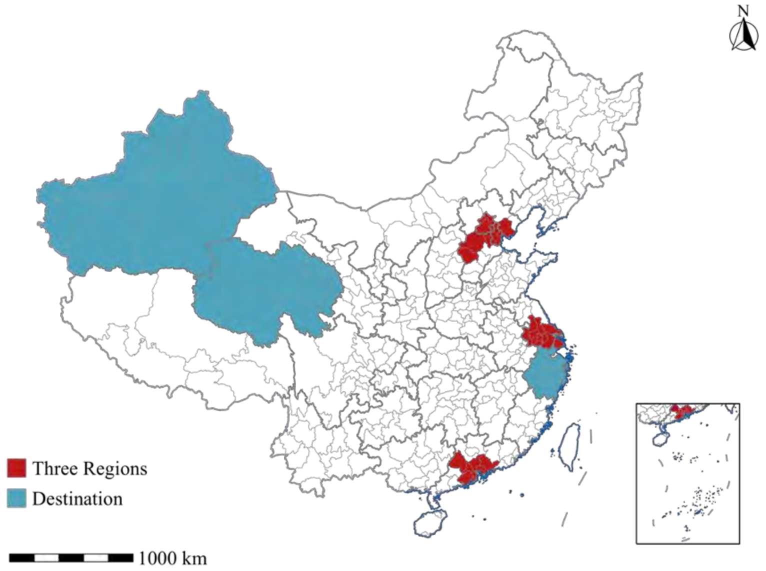
To identify where pollution leakage occurs, we first analyze the destinations that received pollution-intensive investments. Our findings in Section 5.1 indicate that the Clean Air Policy may have had a greater impact on firms in the Three Regions than in the Ten City Clusters, implying distinct relocation patterns. To account for this heterogeneity, we split the treatment groups and estimate the following model:

$$Y_{ijt} = \beta_0 + \beta_1 policy_{ijt}^{regions} + \beta_2 policy_{ijt}^{clusters} + (\boldsymbol{s_c} \square \mu_t)'\boldsymbol{\psi} + \lambda_i + \lambda_j + \mu_t + \lambda_{ij} + \delta_{zt} + \theta_{pt} + \varepsilon_{ijt} \quad (6)$$

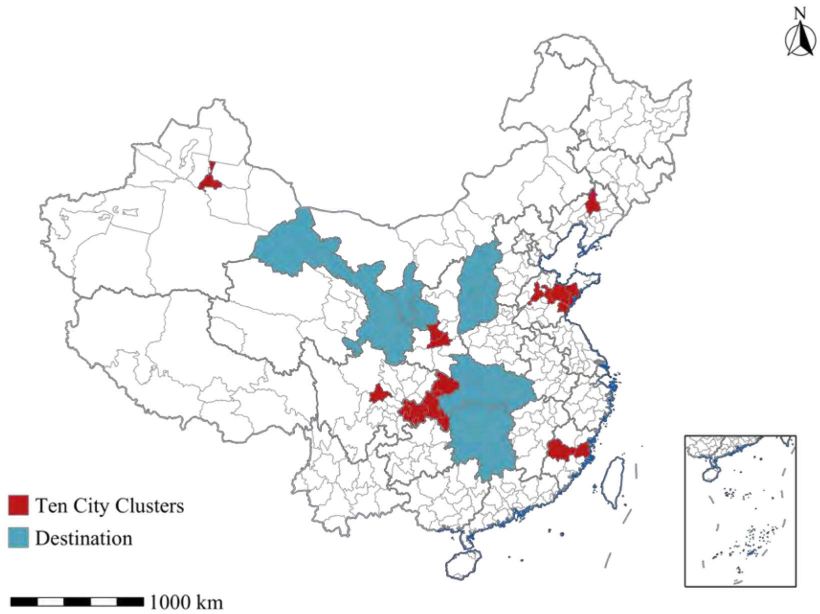
where Y_{ijt} represents pollution leakage from firm *i* to recipient city *j* in year *t*. $policy_{ijt}^{regions}$ and $policy_{ijt}^{clusters}$ are indicator variables for firms in the Three Regions or Ten City Clusters respectively. $\boldsymbol{s_c}$ includes pre-treatment characteristics of the polluter cities[9]. λ_i are firm fixed effects, λ_j are recipient city fixed effects, μ_t are year fixed effects. λ_{ij} are firm-recipient fixed effects, δ_{zt} are industry-by-year fixed effects and θ_{pt} are province-by-year fixed effects. ε_{ijt} are standard errors.

We estimate Equation (6) for different provinces to determine whether a specific province became a destination for pollution leakage. A statistically significant coefficient indicates that the province received pollution-intensive investment due to the Clean Air Policy, while an insignificant coefficient suggests otherwise. To illustrate the provincial distribution of pollution leakage, we highlight the affected provinces in Figure 4. Our results show distinct relocation patterns: Firms in the Three Regions primarily relocated pollution-intensive investments to both nearby provinces and western China. Firms in the Ten City Clusters predominantly shifted pollution to central regions. These findings indicate that pollution leakage is not merely a localized phenomenon but can extend across longer distances, potentially influenced by regional economic conditions, industrial structures, and transportation networks.

[9] Since λ_j has already absorbed the time-invariant characteristics of the recipient cities, we do not include pre-treatment characteristics of recipient cities.



(a)



(b)

Figure 4. Destination patterns of pollution leakage

Notes: Subplot (a) depicts the preferable province for firms in Three Regions and subplot (b) depicts the counterpart for firms in Ten City Clusters.

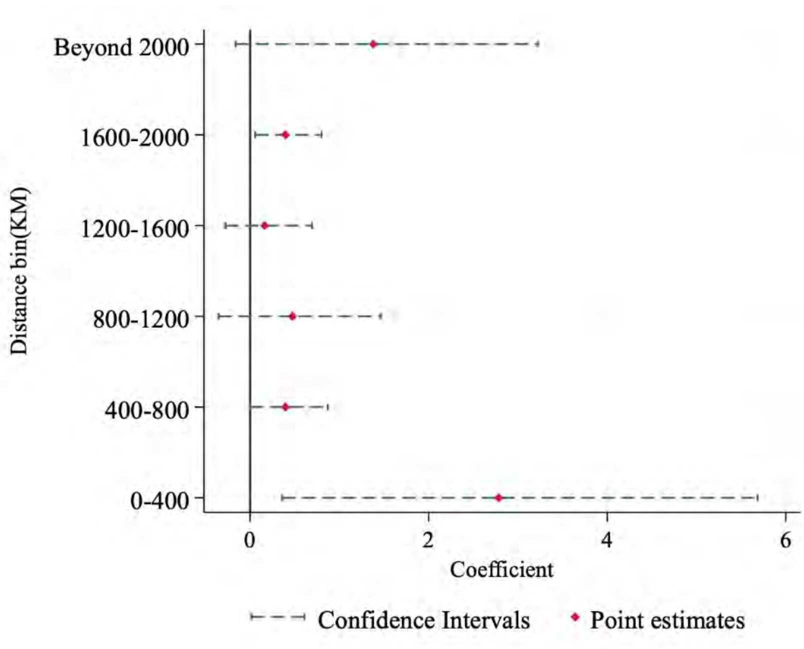
5.2.2 Distance for pollution leakage

Another important element in our analysis is determining the preferred relocation distance for pollution-intensive investment. We begin by calculating the distance between each firm and its subsidiaries. Figure A1 shows that the maximum observed distance is approximately 4,000 km, which we adopt as the upper bound, dividing the range into 400 km intervals. Given the limited number of investments beyond 2,000 km, we group all relocations beyond this threshold into a single category. To assess whether firms in the Three Regions and Ten City Clusters differ in their preferred investment distances, we divide the treatment group and estimate the following model:

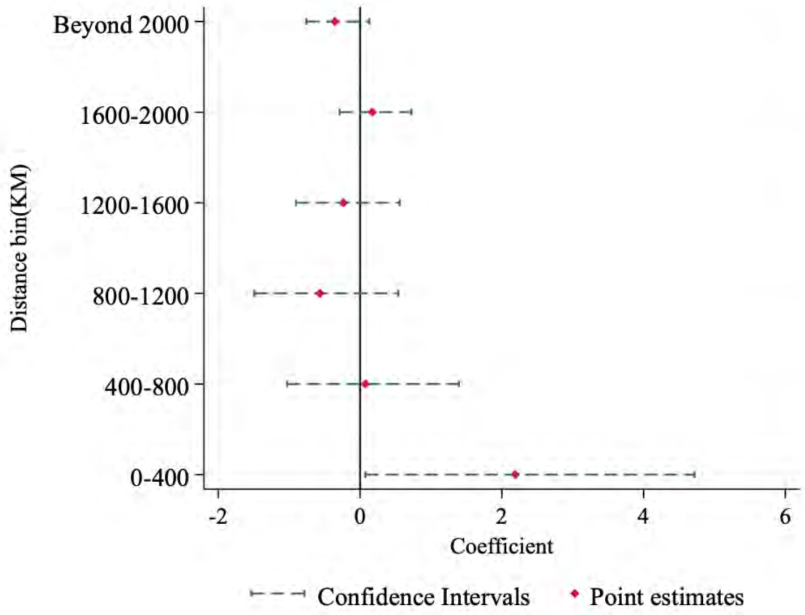
$$Y_{idt} = \beta_0 + \beta_1 policy_{idt}^{regions} + \beta_2 policy_{idt}^{clusters} + (\boldsymbol{s_c} \times \mu_t)'\boldsymbol{\psi} + \lambda_i + \mu_t + \delta_{zt} + \theta_{dt} + \varepsilon_{idt} \qquad (7)$$

where Y_{idt} represents pollution leakage investment from firm i at distance d in year t; $policy_{idt}^{regions}$ and $policy_{idt}^{clusters}$ are indicator variables for firms in the Three regions and Ten City Clusters, respectively; θ_{dt} are distance-bin fixed effects interacted with year fixed effects to control for time-varying distance-related factors; All other specifications follow Equation (6).

We estimate Equation (7) for different distance bins to determine the preferred investment distance. A statistically significant coefficient for $policy_{idt}^{regions}$ or $policy_{idt}^{clusters}$ indicates that firms in the Three Regions or Ten City Clusters tend to relocate investment within this distance bin. Figure 5 plots the estimated coefficients and their 90% confidence intervals. The results reveal distinct relocation patterns: Firms in the Three Regions significantly increased investment in (0 km, 400 km] and (1,600 km, 2,000 km] bins, indicating both short- and long-distance relocation. Firms in the Ten City Clusters showed a significant increase only in the (0 km, 400 km] bin, suggesting that their relocation strategies were largely localized. While previous studies suggest that pollution-intensive investments typically relocate within 450 km (Du et al., 2025), our findings extend this conclusion by showing that firms in the Three Regions also shift investments westward over much longer distances.



(a)



(b)

Figure 5. Distance pattern for pollution leakage

Notes: Error bars represent 90% confidence intervals. The subplot (a) displays investment distances for firms in the Three Regions, while the subplot (b) shows investment distances for firms in the Ten City Clusters.

5.3 Moderators of pollution leakage

To gain deeper insight into the mechanisms driving pollution leakage, we examine factors that moderate the relationship between environmental regulation and investment shifts. These factors are analyzed at both the recipient city and firm levels to explain variation in pollution-intensive investment relocation.

5.3.1 City characteristics

One important city-level factor is industrial agglomeration, defined as the geographic concentration of firms across industries, which can reduce transport costs and improve productivity (Ellison et al., 2010). Cities with well-developed industrial agglomerations and strong external economies tend to be more attractive to pollution-intensive firms, as they offer access to suppliers, skilled labor, and infrastructure (Lin and Zhang, 2023). Consequently, we expect industrial agglomeration to positively moderate the effect of the Clean Air Policy on pollution leakage. To test this hypothesis, we estimate the following model:

$$Y_{ijt} = \beta_0 + \beta_1 policy_{ijt} + \beta_2 policy_{ijt} \cdot agg_{jz} + (\boldsymbol{s_c} \cdot \mu_t)'\boldsymbol{\psi} + \lambda_i + \lambda_j + \mu_t + \lambda_{ij} + \delta_{zt} + \theta_{pt} + \varepsilon_{ijt} \quad (8)$$

Where agg_{jz} represents the degree of industrial agglomeration for industry z in recipient city j, measured by the number of firms in that industry based on the 2012 Annual Survey of Industrial Firms. The coefficient β_2 captures whether cities with stronger industrial agglomeration attract more pollution investment under the Clean Air Policy. The results, presented in Column (1) of Table 7, show that β_2 is positive and significant at the 10% level, confirming that cities with greater industrial agglomeration receive more pollution-intensive investments.

Another critical factor influencing potential investment location decisions is transportation infrastructure. Cities with well-developed transportation systems facilitate the movement of goods and materials, making them more appealing to pollution-intensive firms (Li et al., 2021). To examine this, we use road area as a proxy for transportation capacity and estimate the following model:

$$Y_{ijt} = \beta_0 + \beta_1 policy_{ijt} + \beta_2 policy_{ijt} \times trans_j + (\boldsymbol{s_c} \times \mu_t)'\boldsymbol{\psi} + \lambda_i + \lambda_j + \mu_t + \lambda_{ij} + \delta_{zt} + \theta_{pt} + \varepsilon_{ijt} \quad (9)$$

Where $trans_j$ represents the total road area in recipient city j, collected from the *2012 China City Statistical Yearbook*. Column (2) of Table 7 shows a positive and statistically significant coefficient at the 10% level, suggesting that cities with better transportation infrastructure are more likely to receive pollution-intensive investment from key areas.

5.3.2 Firm characteristics

At the firm level, the existing subsidiary network plays an essential role in shaping relocation decisions. Establishing operations in a new city often entails regulatory uncertainty and the need to coordinate with local authorities, whereas firms with existing subsidiaries can leverage pre-existing resources, supply chains, and familiarity with regulations. To examine whether firms prefer to invest in cities where they already have subsidiaries, we estimate the following model:

$$Y_{ijt} = \beta_0 + \beta_1 policy_{ijt} + \beta_2 policy_{ijt} \times net_{ij} + (\boldsymbol{s_c} \times \mu_t)'\boldsymbol{\psi} + \lambda_i + \lambda_j + \mu_t + \lambda_{ij} + \delta_{zt} + \theta_{pt} + \varepsilon_{ijt} \quad (10)$$

Where net_{ij} represents the number of pre-existing subsidiaries of firm i in recipient city j in 2012, which is a proxy for firms' subsidiary networks. As shown in Column (3) of Table 7, the interaction term β_2 is positive and significant at the 1% level, confirming that firms are more likely to reinvest in cities where they already have subsidiaries, as familiarity with the local business environment reduces entry and transaction costs.

In addition to external factors, firm capability plays a critical role in shaping both compliance with environmental regulations and the incentive for regulatory arbitrage. More capable firms are better equipped to meet regulatory standards without sacrificing profitability, while less capable firms may incur higher compliance costs. Among various capabilities, innovation is particularly important in reducing such costs. Firms with higher R&D intensity are more likely to develop cleaner technologies and optimize production, reducing reliance on pollution-intensive operations. In contrast, firms with weaker innovation capacity may struggle to meet stricter standards and thus face stronger incentives to shift production to less-regulated areas. To test this hypothesis, we follow Li and Zhou (2017) and use R&D expenditures in

2012 as a proxy for firm innovation. The model specification is:

$$Y_{it} = \beta_0 + \beta_1 policy_{it} + \beta_2 policy_{it} \cdot RD_i + (\boldsymbol{s_c} \cdot \mu_t)'\boldsymbol{\psi} + \lambda_i + \mu_t + \delta_{zt} + \theta_{pt} + \varepsilon_{it} \qquad (11)$$

Where RD_i represents the R&D expenditures of firm *i* in 2012. The results in Column (4) of Table 7 indicate β_2 is negative and significant at the 1% level, suggesting that weaker innovation capabilities increase the likelihood of firms relocating their pollution-intensive activities. This suggests that firms with limited technological capacity may fail to meet environmental standards and instead relocate to circumvent stricter regulations.

Table 7. Moderators of pollution leakage

	City-level factors		Firm-level factors	
	Industrial agglomeration (1)	Transportation infrastructure (2)	Established network (3)	Innovation capacity (4)
policy	0.003	0.000	0.003	3.916***
	(0.004)	(0.004)	(0.004)	(0.895)
policy * moderator	0.005*	0.062*	0.721***	-0.639***
	(0.003)	(0.032)	(0.169)	(0.220)
Control * Year FE	Yes	Yes	Yes	Yes
Firm Fe	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Recipient FE	Yes	Yes	Yes	
Firm-Recipient FE	Yes	Yes	Yes	
Province-Year FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
N	789920	743768	886920	2544
R-sq	0.869	0.873	0.872	0.937

Notes: Dependent variables in all columns are investment. Moderators include industrial agglomeration (*agg*), transportation (*trans*), subsidiary network (*net*) and innovation capacity (*RD*) in columns (1)-(4) respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. Standard errors are in the parentheses.

6. Conclusions and policy implications

Pollution leakage occurs when firms relocate polluting activities to less-regulated regions to reduce their compliance costs. Traditional metrics based on production or emissions may not always be feasible, especially in developing countries with limited data. Investment flows offer a valuable alternative, yet existing measures such as subsidiary counts lack precision. This study leverages manually collected investment data from annual reports of listed pollution-intensive firms to provide a more accurate assessment. Applying this dataset and the DID method, we evaluate pollution leakage triggered by China's 2013 Clean Air Policy. The main findings are summarized as follows:

First, the policy significantly increased pollution leakage from key areas to less-regulated regions. Regulated parent firms in the key areas reduced output while simultaneously increasing pollution-related investments in their subsidiaries located in less-regulated areas after the policy, supporting the presence of pollution leakage. Second, the effects are more pronounced in the Three Regions than in the Ten City Clusters, leading to distinct relocation patterns. Firms in the Three Regions shift pollution-intensive investments to both nearby provinces and distant western China, while those in the Ten City Clusters mainly move to nearby, usually in central China. Spatially, firms in the Three Regions concentrated their investments in a bimodal manner with peaks at (0, 400] km and (1,600, 2,000] km, while firms in the Ten City Clusters mainly relocated within <400 km. These findings indicate that pollution leakage is not necessarily restricted to short distances. Finally, both city- and firm-level characteristics moderate the extent of pollution leakage. Cities with greater industrial agglomeration and better transportation infrastructure attract more pollution-intensive investments, reflecting firms' preference for locations with established supply chains and logistical efficiency. At the firm level, investments are more likely to shift towards cities with existing subsidiaries, suggesting a role for coordination cost reduction. Firms with lower innovation capacity are more likely to relocate emissions, reflecting their limited ability to comply through technological upgrading.

These conclusions lead to several policy recommendations: First, regulators should strengthen environmental disclosure standards for listed firms' subsidiaries. Our findings show that intra-group investment shifts are a key channel for pollution leakage, especially within large corporate networks. Tougher subsidiary-level reporting requirements would improve transparency and enforcement.

Second, policymakers should proactively address pollution leakage driven by regionally differentiated environmental regulations by supporting mitigation efforts in less-regulated areas. Our findings confirm that pollution has shifted from eastern to central and western regions, closely following the relocation of investment. This pattern is largely shaped by regional economic disparities and differences in regulatory capacity. While central and western provinces may gain economically from this shift, they often lack the infrastructure and governance needed to manage the associated environmental pressures. Although transferring emissions from heavily polluted eastern regions to relatively cleaner areas may reduce marginal harm, it does not justify unchecked relocation. To prevent long-term environmental degradation and regional inequality, the central government should strengthen policy coordination and provide targeted funding to support emission reduction efforts in central and western China, with a particular focus on building early-stage pollution control infrastructure and strengthening institutional capacity.

Furthermore, as regions with strong industrial agglomeration and transport networks tend to attract more pollution-intensive investments, local governments should enhance environmental oversight to impede emission clustering. Encouraging innovation in pollution-intensive firms can also help curb investment-driven leakage. The central government should promote technological green upgrading by incentivizing pollution control technologies.

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Appendix

Table A1. Balancing Test

Variable	Before matching			After matching		
	Control	Treatment	Mean-Diff.	Control	Treatment	Mean-Diff.
	N = 188	N = 223		N = 172	N = 218	
ROA	6.707	6.655	0.052	6.702	6.690	0.012
Net profit margin	8.020	6.621	1.399	6.709	6.669	0.040
Debt-to-Asset ratio	51.932	49.500	2.432	50.571	48.883	1.687
Equity ratio	0.464	0.554	-0.091	0.451	0.466	-0.015
Revenue growth rate	2.526	1.209	1.317*	1.411	1.263	0.149
Tobin Q	34.081	27.929	6.152	30.348	28.136	2.212
Fixed asset ratio	1.942	1.981	-0.039	1.929	1.991	-0.062
Age	0.368	0.350	0.018	0.368	0.346	0.023
(log) Employee	13.324	14.072	-0.747*	13.215	13.977	-0.762*
(log) Total asset	21.908	21.907	0.001	21.925	21.838	0.087

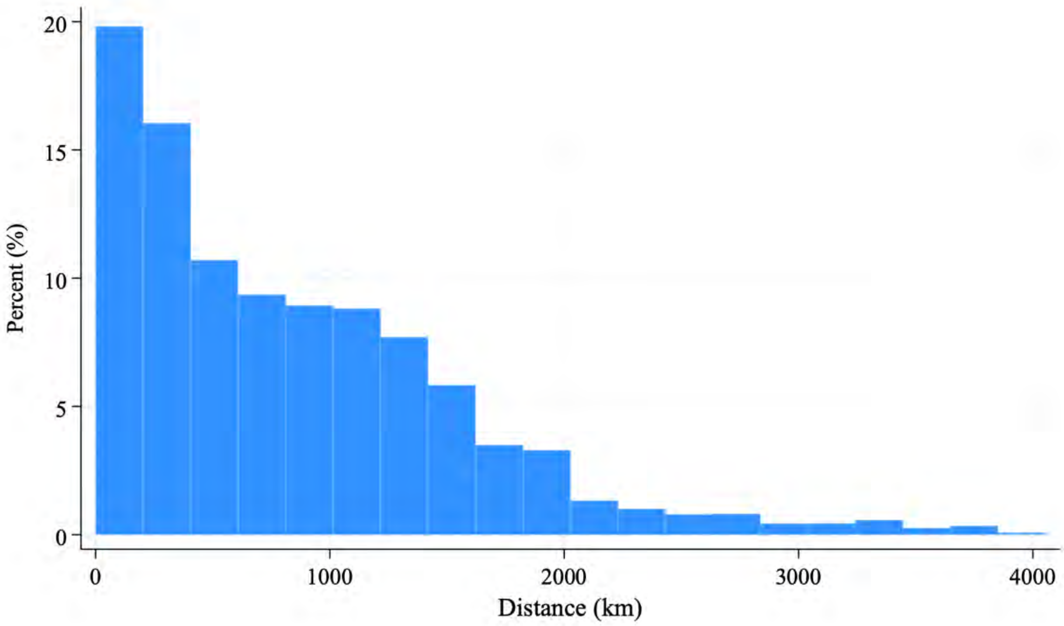

Figure A1. Distance between parent firms and their subsidiaries