Pollution Haven Next Door: Evidence from China

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Abstract

The Pollution Haven Effect (PHE) predicts that environmental regulation shifts pollution-intensive production toward less regulated regions. This paper tests the PHE within a single country by examining the Key Cities Air Pollution Control policy, a city-specific air quality program in China. Using a synthetic difference-in-differences design to correct for targeted policy placement, I estimate the policy's effects on sulfur dioxide (SO_2) emissions and industrial composition in treated and neighboring cities. The results reveal limited overall emission reductions but clear evidence of spatial reallocation: under half a decade, treated cities shift pollution toward cleaner sectors, while neighboring cities expand output and capital in pollution-intensive industries, consistent with inter-city pollution leakage. Further analysis shows that this reallocation was driven largely by provincial governments strategically using state-owned enterprises to redistribute production, with a secondary role for firm-level product switching. These findings demonstrate that environmental regulation can generate PHE-type outcomes in short term, driven by non-market forces, and that well-intentioned policies may reshape regional industrial structures in unintended ways.

Keywords: Pollution Haven Effect, China, Regional Environmental Regulation, Industrial Structure

JEL Codes: F18, Q52, Q56, Q58, R11

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1 Motivation and Introduction

Environmental regulations are often designed within political boundaries, but their economic and environmental consequences rarely stop at the border. As a result, the spatial challenges of environmental regulation have become increasingly salient in both public discourse and academic research (Balboni and Shapiro, 2025). A central concern is the Pollution Haven Effect (PHE), which states that environmental regulation has a negative effect on competitiveness in affected industries, either through shifts in production across regions (Hanna, 2010; Copeland et al., 2022; Chen et al., 2025) or through changes in firms' location choices (Henderson, 1995; Harrison et al., 2015). Taking the interaction between environmental policy and the spatial distribution of economic activity into account is critical in order to design effective regulation. Improvement in environmental outcomes in one location may come at the expense of others.

Although the PHE has been widely studied, empirical support for a drastic change in industrial structure remains limited. Most existing work at cross country level finds limited support for structural shifts (Copeland et al., 2022; Levinson, 2023; Shapiro and Walker, 2018), with the notable exception of a case study on the battery recycling industry between the United States and Mexico (Tanaka et al., 2022). One explanation for the absence of strong evidence is that high cross-country trade costs and productivity differences can offset the comparative advantage effects created by environmental regulation (Duan et al., 2021).

This paper revisits the PHE in a subnational context, studying how environmental regulation can reshape the industrial composition of cities within the same national economy. I examine the impact of the Key Cities for Air Pollution Control (KCAPC) program in China — a national air quality program that targets selected cities — on the performance of polluting and less-polluting sectors in both regulated cities and their neighbors. I aim to answer the following questions: (i) What is the magnitude of regulation-induced reallocation? (ii) How do firms respond to / circumvent regulation? (iii) If there is a reallocation, is it driven by market forces or by non-market (political) mechanisms?

China offers an ideal setting for such analysis. First, its rapid economic growth has been accompanied by severe environmental degradation, making it a relevant case for assessing the effectiveness of environmental regulation. Second, its vast geographic and economic diversity enables subnational analysis at a scale comparable to cross-country studies, while avoiding confounding factors such as stark institutional differences. This helps isolate potential reasons why the change in industrial structure may not emerge at the cross-country level. Taken together, these features make China a particularly informative context for studying the mechanisms of the PHE.

I focus on the second round of the KCAPC policy, implemented in 2002 across 66 cities. An earlier round in 1998 targeted 47 other cities, but data limitations prevent a comparable analysis. Before implementation in 2001, the surveyed firms in the second round cities accounted for about 21 % of national manufacturing output and 30 % of manufacturing-related sulfur dioxide (SO_2) emissions, the main focus of this paper.[1]

The analysis draws on two main firm-level datasets: the Annual Environmental Survey of Polluting Firms (AESPF) and the Annual Survey of Industrial Firms (ASIF). The AESPF, conducted by the Ministry of Environment, covers firms responsible for the top 85% of county-level emissions and reports detailed pollutant data, including SO_2 emissions. The ASIF includes all state-owned firms and non-state-owned firms with annual revenues above 5 million RMB, providing comprehensive financial, operational, and locational data. Merging these datasets yields a city-sector panel from 1998–2007 for evaluating the KCAPC's effects on environmental performance, industrial composition, and economic structure.

To estimate causal impacts, I apply the synthetic difference-in-differences (SDID) method proposed by Arkhangelsky et al. (2021), which combines synthetic control and difference-in-differences to address non-random treatment selection and heterogeneous pre-trends. I

[1]Sulfur Dioxide (SO_2) emissions in manufacturing production are mostly through the burning of fossil fuel that contains sulfur, such as coal or oil, or industrial processes such as extracting metal from ore, producing petrochemicals, etc. Short-term exposure to SO_2 can harm the human respiratory system and make breathing difficult. Also, SO_2 reacts in the air to form particulate matter (PM) that penetrates into the lungs and causes health problems. For more details, see EPA Sulfur Dioxide Basics.

examine both aggregate effects and heterogeneous impacts across sectors, distinguishing between the top-quintile most pollution-intensive industries (ranked by SO_2 intensity, hereafter, "polluting sectors") and less-polluting industries. To provide further evidence for the PHE, I also investigate changes in neighboring, non-treated cities. In both analyses, I construct the control group from distant, non-neighboring cities.

Separately estimating the impact of KCAPC for treated and non-treated neighboring cities that are potentially exposed to policy-induced spillovers relative to far-off non-treated cities is important both theoretically and empirically. By excluding potentially contaminated neighbors, my research design reduces bias in the estimated effects for treated cities. Moreover, analyzing neighboring cities separately allows me to test whether spatial spillovers operate through the PHE channel directly. In this way, the approach complements prior firm-level studies of KCAPC (Liu et al., 2021; Viard et al., 2022) that rely on geographically proximate controls and help reconcile differences in findings.

Using this framework, I document that the policy targets polluting sectors more aggressively, and find evidence supporting the PHE in both treated cities and their neighboring areas. In treated cities, the KCAPC reduces emission intensity in polluting sectors and shifts SO_2 emissions toward less-polluting sectors. In terms of economic outcomes, I observe a substantial increase in output for less polluting sectors and a more modest increase for polluting sectors. However, there is no significant effect on differential growth patterns, suggesting that KCAPC led to a shift in pollution composition (i.e., due to cleaner production process from polluting sectors) rather than a reallocation of economic specialization. The effects are more pronounced in neighboring cities. Compared to distant control cities, neighboring areas experienced significant increases in both total emissions and output, with output growth mainly driven by polluting sectors. My results are robust to different specification checks, such as a placebo test with randomly assigned treatments and sectors, excluding outliers, controlling for different fixed effects, etc.

To better understand the mechanisms driving these patterns, I assess three channels:

within-firm product adjustment, extensive-margin dynamics (entry and exit), and non-market forces. The evidence points primarily to the third channel.

First, I document "switching" among treated city firms that reallocate production toward less pollution-intensive products; excluding these firms leaves the baseline patterns essentially unchanged. Second, while polluting sectors in treated cities exhibit somewhat higher exit and lower net entry, these effects are quantitatively small, indicating that extensive-margin dynamics play a limited role. Third, ownership-based heterogeneity shows that reallocation is largely driven by state-owned enterprises (SOEs): SOEs expand in less polluting sectors within treated cities and in polluting sectors in neighboring cities, whereas effects for non-SOEs are small and statistically insignificant. Taken together, these results suggest that the KCAPC policy induced reallocation primarily through non-market mechanisms operating via SOEs, rather than through within-firm product switching or entry–exit responses.

The mechanisms uncovered in this paper, such as selective enforcement on limited sectors, cross-jurisdictional leakage, and politically mediated industrial reallocation, are not unique to China's governance system. Recent empirical evidence from the US documents that firms subject to the Clean Air Act's (CAA) attainment designations offset regulated air releases by increasing discharges in plants elsewhere (Gibson, 2019). More recently, the Good Neighbor Plan (GNP)[2] was issued in 2023 that targeted selected upwind states and industries on NO_X emissions. Although the pollutants differ, my findings on SO_2 under the KCAPC highlight how uneven enforcement in regional caps can create "pollution havens" nearby.

This paper contributes to the literature on the Pollution Haven Effect (PHE) and, more broadly, on leakage from environmental regulation (Antweiler et al., 2001; Barrows and Ollivier, 2021; Becker and Henderson, 2000; Curtis et al., 2025; Duan et al., 2021; Levinson, 2009, 2023; Tanaka et al., 2022). See Copeland et al. (2022) for a comprehensive review. Most cross-country studies comparing the global North and South find limited evidence of PHE. Trade-related changes in emissions tend to be driven by changes in aggregate output (Barrows

[2]For more details, see Good Neighbor Plan for 2015 Ozone NAAQS.

and Ollivier, 2021) or in pollution intensity (Cherniwchan, 2017; Holladay, 2016; Najjar and Cherniwchan, 2021; Shapiro and Walker, 2018), rather than by large shifts in industrial structure. Within-country work often relies on conditional logit models of location choice (Wu et al., 2017; Wang et al., 2019; Yang et al., 2018), which present challenges for causal identification and policy counterfactuals. This paper complements the existing literature from the following aspects. First, I explicitly identify reallocation toward neighboring (non-treated) cities as a plausible destination for displaced activity, and causally estimate the reallocation effect and policy effect using SDID. Second, I show that changes in industrial composition can emerge over a relatively short horizon, plausibly reflecting political channels through SOEs, rather than the slower market-driven adjustments emphasized in prior work (Curtis et al., 2025).

This paper also contributes to the literature on firms' responses to environmental regulation. Theoretical models suggest that polluting and non-polluting firms may exhibit different location patterns and stratify into different cities facing regulation (Lange and Quaas, 2007; Kyriakopoulou and Xepapadeas, 2013). Empirical studies document that firms respond by upgrading their production processes (Fan et al., 2025; Liu et al., 2021; Shapiro and Walker, 2018) or by circumventing regulation through shifting pollution-intensive activities to unregulated firms, outsourcing to other countries (Ben-David et al., 2021; Hanna, 2010), within a country (Fowlie, 2009), or reallocating production within conglomerates (Chen et al., 2025; Cui et al., 2023; Curtis et al., 2025; Gibson, 2019). The finding in Gibson (2019) is closely related to this paper. Making use of the conditional exogeneity on non-attainment status and monitor locations, Gibson (2019) studies the effect of regulation from the CAA on firms' pollution input and finds that regulated firms double their water emissions instead. Compared to their findings about regulation-induced substitution between pollution input, this paper focuses on the substitution between products of different pollution intensity: firms mitigate regulatory pressure by shifting their primary production toward less pollution-intensive products.

Finally, this paper contributes to the literature on heterogeneous environmental regulation stringency and the principal-agent problem in environmental governance. Prior research documents that local governments in developing countries often face weak institutions or prioritize economic growth (Duflo et al., 2013; Du and Li, 2023), which can lead to uneven enforcement of environmental regulations across regions. A related strand of literature shows that environmental regulations tend to be more lenient in border areas (Cai et al., 2016; Lipscomb and Mobarak, 2016; Monogan III et al., 2017). This study further identifies that provincial governments strategically reallocate production through state-owned enterprises, which expand in cleaner sectors within regulated cities and in more polluting sectors in neighboring ones. These findings differ from those in Chen et al. (2018), who document city governments trading off economic mandates for environmental performance. This paper highlight how effectiveness of policy depend on whether the unit of regulation aligns with the unit of coordination instead.

The remainder of the paper is organized as follows. Section 2 reviews the KCAPC policy. Section 3 describes the datasets. Section 4 outlines the empirical strategy. Section 5 reports the main results for treated cities and their neighboring cities. Section 6 explores the underlying mechanisms. Section 7 concludes.

2 Policy Background

In response to increasingly severe pollution problems, China introduced a dedicated environmental protection plan in its Tenth Five-Year Plan.[3] Among the initiatives launched under this framework was the Key Cities for Air Pollution Control (KCAPC) policy, one of the major air quality regulations implemented by the Ministry of Environmental Protection (MEP) to curb urban air pollution.

The KCAPC policy was first launched in 1998 and expanded later with the objective of improving air quality in key urban areas. The central government initially designated

[3] For the official document, see National Environmental Protection 10th Five-Year Plan (in Chinese).

47 prefecture-level cities — primarily provincial capitals, special economic zones, and major tourist destinations — as the first batch of targeted cities. A second batch of 66 additional cities was designated in December 2002 under the Tenth Five-Year Plan.[4] These cities were required to meet specific air quality targets by 2005, based on China's Class II Air Quality Standard (GB3095-2000) for SO_2 and five other pollutants.

The second-round cities were selected primarily based on their failure to meet the GB3095-2000 air quality standard in the year 2000, along with additional criteria. After a comprehensive assessment of contemporaneous pollution levels and city-level economic conditions, 66 cities were chosen for inclusion in the KCAPC. The selection was guided by three main considerations: (1) overall levels of economic development and environmental pollution; (2) inclusion in the Two Control Zones (TCZ), another major national policy targeting SO_2 emissions at the city level;[5] and (3) cities with cultural heritage deemed in urgent need of environmental protection. The spatial distribution of both the first and second batches of KCAPC cities is shown in Figure 1. The map reveals a strong concentration of designated cities in the more industrialized eastern and central provinces, with relatively sparse coverage in the west. This geographic pattern is consistent with the policy's focus on large urban industrial emitters and areas with higher administrative capacity.

To comply with the air quality standards, the selected cities were subject to a range of regulatory instruments outlined in a follow-up directive.[6] Provincial and treated city governors were instructed to restructure the industrial base by shutting down, suspending, or relocating highly polluting firms, especially those with outdated technology, high energy consumption, and excessive emissions. Firms were required to install online monitoring equipment and adopt cleaner energy sources such as electricity, natural gas, and liquefied petroleum gas. The policy promoted reducing raw coal consumption, introducing clean coal

[4]For the official document, see Plan for Designating Key Cities for Air Pollution Prevention and Control (in Chinese).

[5]The Two Control Zones (TCZ) policy targets both total SO_2 emissions and acid rain control.

[6]For the official document, see National Plan for Pollution Prevention and Control, 2003–2005 (in Chinese).

technologies, establishing high-pollution fuel ban zones, and providing financial support for production upgrades.

Empirical research has found that the KCAPC policy significantly reduced pollution in the targeted cities (Liu et al., 2021; Viard et al., 2022), largely because city governments were incentivized to enforce the regulations described above. Cities in the first batch were assessed directly by the MEP, while those in the second batch were evaluated by provincial environmental protection bureaus, which in turn reported their assessments to the MEP.

As stated in the Tenth Five-Year Plan, environmental protection was the responsibility of local governments. This was formalized through "letters of responsibility" signed by mayors, specifying environmental goals for their term.[7] Performance was reported to the MEP, and state media published daily air quality data for these cities. Environmental outcomes could directly influence officials' political evaluations and promotion prospects, further motivating enforcement. These same incentives, however, could also create incentives to relocate pollution-intensive activities to neighboring jurisdictions, raising the possibility of cross-border leakage effects.

Additionally, KCAPC policy targeted certain polluting industries more aggressively than others, as outlined in the Tenth Five-Year Plan. The plan emphasized controlling pollution from key sectors such as metallurgy, petrochemicals, cement, paper products, and the textile industry. In a subsequent review report,[8] the government highlighted efforts to promote technological upgrades in these industries, claiming that total output in these sectors continued to grow while their pollution intensity declined.

Due to data availability constraints, this study focuses on the second round of the policy implemented in 2002.

[7] For official document, see Urban Environmental Protection in China (in Chinese).

[8] See China's Environmental Protection (1996–2005) (in Chinese) from the State Council Information Office.

3 Data

3.1 Annual Survey of Industrial Firms

I use the Annual Survey of Industrial Firms (ASIF) to construct city- and sector-level economic outcomes for the period 1998 to 2007. This dataset covers all state-owned enterprises (SOEs) and non-state-owned enterprises with annual sales exceeding 5 million RMB (approximately 696,000 USD). The "industry" is defined following China's National Industrial Classification to include three categories: mining, manufacturing, and the utilities (production and supply of electricity, gas, and water). Collected by the National Bureau of Statistics (NBS), ASIF includes detailed firm-level accounting information, which is also used to compile aggregated industrial statistics in the China Statistical Yearbook.

ASIF is widely used in empirical research on the Chinese economy. I follow established practices to clean the data. In particular, I drop observations with missing or negative values for key financial variables such as output, employment, and capital stock. I also drop observations that violate basic accounting consistency, such as firms reporting liquid assets, fixed assets, or net fixed assets that exceed total assets, or current depreciation that exceeds cumulative depreciation. These procedures follow the guidelines in Yu (2015) and Brandt et al. (2012).

Using the cleaned dataset, I construct measures of total gross sales revenue, capital stock, employment, and the number of firms at the city-sector-year level. I also use the average wage to control for potential differences in labor cost.

3.2 Annual Environmental Survey of Polluting Firms

The Annual Environmental Survey of Polluting Firms (AESPF)[9] is the most comprehensive firm-level environmental dataset available in China. Conducted by the Ministry of Envi-

[9]This dataset is also referred to as the China Environmental Statistics Dataset (CESD) (Liu et al., 2021; Zhang et al., 2018) or the Environmental Survey and Reporting Database (ESRD) (He et al., 2020).

ronment, the survey provides detailed information on firms' environmental performance, including emissions of major pollutants, use of pollution abatement equipment, and energy consumption. Key pollutants include SO_2, the primary focus of the KCAPC and this paper, as well as chemical oxygen demand (COD), ammonia nitrogen, industrial smoke, dust, and solid waste.

Firms are included in the survey if their emissions rank among the top 85 percent of total emissions for a given pollutant at the county level. Emission data are initially self-reported by firms but are subject to random audits and verification by both national and provincial environmental agencies before inclusion in the dataset. To ensure truthful reporting, the Environmental Protection Law prohibits the use of this data as a basis for regulatory penalties, reducing firms' incentives to misreport (He et al., 2020).

Similar to the Annual Survey of Industrial Firms (ASIF), which underlies macroeconomic indicators, the AESPF serves as the micro-level foundation for environmental statistics reported in the China Statistical Yearbook on Environment. Fan et al. (2025) compares aggregated pollution indicators from the AESPF to those in the Yearbook and finds them to be highly consistent.

This paper uses firm-level data on SO_2 emissions and total (pre-abatement) generation[10] to construct environmental outcome measures.

3.3 Other Data Sources

Additional city-level information is obtained from the China City Statistical Yearbook (CCSY), an annual publication produced by the National Bureau of Statistics of China. The CCSY provides comprehensive socioeconomic statistics for municipal-level cities. In this study, I use data on population and GDP per capita from the CCSY. When these variables are missing, which happened occasionally for small cities before 2000, I supplement the data using

[10] SO_2 generation refers to the quantity produced before any end-of-pipe control. The AESPF dataset records both emitted SO_2 and SO_2 removed by on-site abatement; total generation equals the sum of these two amounts.

information from city government annual reports.

Information on whether a city is included in the KCAPC program is obtained from official government documents and policy notices.

3.4 Merging Datasets

I use the ASIF dataset to examine the impact of the KCAPC policy on the aggregate economic structure, and the merged ASIF–AESPF dataset to analyze its effect on environmental performance. This distinction is necessary because only ASIF contains firms' sector classifications, which are essential for identifying structural changes. In this section, I present descriptive statistics for both the full ASIF sample and the merged sample.

Following the procedure in Liu et al. (2021), I merge the AESPF and ASIF datasets using each firm's unique identifier and name without fuzzy matching. I restrict the analysis to manufacturing firms, dropping firms in the mining and utilities sectors. Figure 2 shows the number of matched firms (left) and the corresponding match rate (right) for each year. Approximately 13–20 percent of ASIF firms and 38–48 percent of AESPF firms are successfully matched. The AESPF match rate is consistent with previous literature.

Table 1 reports the number of firms, total gross value of output and SO_2 emission for the ASIF, AESPF, and merged datasets by year. Columns 1, 3, and 5 report statistics for the full ASIF (or AESPF) dataset, while Columns 2, 4, and 6 present the corresponding share of the merged sample accounts for. Despite the relatively low match rate on the ASIF side (13–20 percent), the matched firms account for 30–40 percent of the total gross value of output, indicating that the merged sample is skewed toward larger firms. As for SO_2 emission, the merged dataset roughly accounts for a quarter of the emission. This is lower than the share of output, which could be due to larger firms being cleaner as well (Shapiro and Walker, 2018).

Table 2 presents additional descriptive statistics. Column 2 reports SO_2 generation intensity by sector, while Columns 3 and 4 show the share of firms each sector represents in the ASIF and merged datasets, respectively. These statistics suggest that more polluting sectors are disproportionately represented in the merged sample.

Further, I compare the distribution of firm-level emission intensity, output, and capital labor ratio between the merged dataset and AESPF / ASIF dataset in Figure 3. The distributions support the argument that the merged dataset skews towards bigger firms that are more capital-intensive (which are potentially more pollution-intensive).

This sampling skew has implications for how sectoral pollution intensity is measured. Because I use the merged dataset to calculate pollution intensity and to classify sectors as either polluting or less polluting, the resulting measures primarily reflect the pollution profiles of larger firms. However, what matters for my analysis is the **relative ranking** of sectoral pollution intensity, which remains stable over time. I return to this issue in Section 4.2, where I discuss the classification of polluting versus less-polluting sectors and examine the robustness of the ranking-based approach.

4 Empirical Strategy

4.1 Synthetic Difference-in-Difference

As discussed in the Section 2, the cities selected for the KCAPC policy were not randomly assigned. Consequently, applying a standard difference-in-differences (DID) approach may yield biased estimates due to potential differences in pre-treatment trends and selection into treatment.

To address this issue and construct a credible counterfactual, I implement the synthetic difference-in-differences (SDID) method developed by Arkhangelsky et al. (2021). SDID is a flexible panel-data approach that combines the strengths of both DID and synthetic control. The DID framework allows treated and control groups to have parallel but non-overlapping pre-trends. From the synthetic control framework, SDID assigns unit-specific and time-specific weights to optimally construct a control group that closely matches the treated group's pre-treatment trends.

This approach generates a set of city and year weights for each control unit, which are then used to construct the synthetic counterfactual. By doing this, SDID directly addresses KCAPC's selection into pollutive, urban areas. A more detailed explanation of the estimation procedure and weight construction is provided in Appendix A.

To estimate the policy's impact, I implement two complementary models. The first examines aggregate outcomes at the city level, while the second explores heterogeneous effects across sectors by distinguishing between highly polluting and less polluting industries in cities. These models allow me to assess both the overall effectiveness of the KCAPC policy and whether it induces structural change consistent with the PHE. The first estimating equation:

$$ln(Y_{ct}) = \delta + \gamma_1 \mathbb{1}\{T_c\} \times Post_t + \sigma_c + \tau_t + \eta_{ct} \tag{1}$$

In this specification, Y_{ct} denotes the outcome variable for city c in year t, such as total SO_2 emission, industrial output, employment, and capital stock. $\mathbb{1}\{T_c\}$ is a treatment indicator equal to 1 if city c is treated. $Post_t$ is a post-treatment dummy equal to 1 for years 2002 and onward. Standard errors are clustered at the city level, consistent with the treatment assignment. This estimator identifies the average treatment effect under the assumption that the weighted synthetic control group provides a valid counterfactual for treated cities.

The second estimating equation:

$$ln(Y_{sct}) = \alpha + \beta_1 \mathbb{1}\{T_c\} \times Post_t + \beta_2 Pol_s \times Post_t + \beta_3 \mathbb{1}\{T_c\} \times Post_t \times Pol_s + \sigma_{sc} + \tau_t + \epsilon_{sct} \tag{2}$$

Here, I further separate outcomes within a city between the top quintile sectors in terms of polluting intensity and the rest, see Section 4.2 for a detailed explanation. In this model, Y_{sct} is the outcome for the aggregate sector s in city c at year t. Pol_s is a dummy that equals

1 for the sector of top quintile pollution intensity in 1998. I include city-sector fixed effects to account for variation such as heterogeneity in baseline industrial composition across cities. If KCAPC alters the economic structure as expected, $\hat{\beta}_3$ should be negative.

It is important to note that not all untreated cities are suitable for inclusion in the control group. Cities that share a border with treated cities may serve as destinations for displaced polluting activities. Including these neighboring cities in the control group could bias the estimated treatment effect upward by contaminating the counterfactual with indirect policy exposure. To address this concern, I exclude all adjacent cities from the control group. The first round of cities is also excluded.

In a complementary analysis, I reclassify these neighboring cities as a separate treatment group to investigate potential spillover effects of the KCAPC policy. Specifically, I re-estimate the same models described above, replacing the treatment indicator $\mathbb{1}\{T_c\}$ with $\mathbb{1}\{N_c\}$, a binary variable equal to 1 for non-treated cities that border a treated city. Both the analysis of directly treated cities and the spillover analysis rely on the assumption that cities more geographically distant from treated areas remain unaffected by the policy.

4.2 Sector Classification and Data Validity Checks

Classify Polluting Sectors. The SDID framework allows me to estimate both aggregate and heterogeneous treatment effects. To examine heterogeneity, I need to operationalize which industries are "polluting" and which are "less-polluting." As noted in Section 3.4, the merged dataset is skewed toward larger firms and polluting sectors, but what matters for the empirical analysis is the **relative ranking** of sectoral pollution intensity. In what follows, I describe how I construct this ranking and classify industries into top-quintile polluting sectors and the remainder, and I show evidence and robustness checks that support such classification.

First, to identify polluting sectors of varying intensities, I use the merged dataset from the baseline year 1998. Sector-level SO_2 intensity is defined as the total SO_2 generated divided by the gross value of output across all firms within each 4-digit sector. To reduce the influence of outliers and low-count sectors, I exclude sectors with fewer than 10 firms in the merged dataset. This filtering yields 308 out of 405 4-digit sectors for the final analysis.

To visualize relative SO_2 intensity across sectors and its persistence over time, I construct a sectoral ranking index based on deciles of SO_2 intensity as of 1998, where a higher decile rank reflects a more pollution-intensive sector. Figure 4 shows that sectors in the top decile are significantly more pollution-intensive than those in lower bins. Also, it shows that sectoral pollution intensity rankings remain broadly stable over time, making the 1998-based classification suitable for capturing persistent pollution characteristics.

To assess whether KCAPC enforcement varies systematically by pollution intensity, I estimate the SDID model separately by quintile of sectoral SO_2 intensity and report the results in Table 3. The estimates reveal that the policy has a statistically significant effect only for sectors in the top quintile. Based on this finding, I classify firms into two categories for subsequent heterogeneity analysis: those in the top quintile (61 out of 308 sectors) and those in the bottom 80 percent.

This empirical classification is consistent with qualitative evidence from official government documents. As noted in Section 2, the Tenth Five-Year Plan explicitly identifies several highly polluting sectors, including paper manufacturing, petroleum processing, chemical manufacturing, pharmaceutical production, non-metallic mineral products, and ferrous and non-ferrous metals, as targets for stricter regulatory oversight. Most of these industries are concentrated within the top quintile of SO_2 intensity in the data. Thus, the classification into top-quintile polluting sectors is both data-driven and aligned with the policy's stated regulatory priorities.

Descriptive Statistics. I construct two datasets: one at the city level for aggregate analysis, and another at the city-sector level to investigate heterogeneous treatment effects. These datasets are aggregated from firms in the 308 selected four-digit manufacturing sectors and exclude all cities from the first round of KCAPC implementation. I also drop observations from three western provinces, Qinghai, Tibet, and Xinjiang, due to their distinct ethnic composition, cultural context, and economic development levels, which set them apart from the rest of the country.

The resulting panel datasets cover a 10-year period from 1998 to 2007 and include 65 treated cities (excluding one from Xinjiang), 128 neighboring cities, and 69 more distant control cities. Table 4 provides definitions for all variables used in the regression analysis.

Table 5 presents summary statistics for the final datasets. As discussed above, I classify cities into three groups: second-round treated cities, neighboring (non-treated but adjacent) cities, and distant control cities. For each group, the table reports the number of observations, the mean and standard deviation of key variables, and the share of activity accounted for by firms in top-quintile polluting sectors. Figure 5 plots the map of cities based on their respective treatment status.

As expected, treated cities exhibit the highest levels of industrial activity, pollution, and number of surveyed firms, followed by neighboring cities and then distant control cities. The latter two groups show smaller differences across economic and environmental indicators. Notably, the share of firms in top-quintile polluting sectors is similar between neighboring and control cities, which supports their use as comparison groups for examining heterogeneous treatment effects.

Match Rate Issue. As mentioned previously, a potential concern is that the merged dataset used in this paper is skewed toward larger firms and more polluting sectors. Although the merged sample is only used to measure environmental outcomes (e.g., SO_2 emissions), it is important to verify that this sampling skew does not bias the estimated treatment effects. The key issue arises only if the degree of skewness differs systematically across treatment groups. To assess this, I conduct two checks.

First, I examine whether treated, neighboring, and control cities have systematically different match rates by estimating the following equation:

$$match_{sct} = \alpha + \beta_1 \mathbb{1}\{T_c\} + \beta_2 \mathbb{1}\{N_c\} + \tau_t + \sigma_s + \epsilon_{sct}, \tag{3}$$

where $match_{sct}$ is the matching rate between the production and emission datasets for sector s, city c, and year t. The results in Table B1 show that the match rate does not differ significantly across treatment groups.

Second, I compare the firm-level distributions of emission intensity, output, and capital–labor ratios across treatment groups (Figure C1). These distributions are similar between treated, neighboring, and control cities, indicating that the merged dataset does not disproportionately represent certain types of firms in any particular group.

Taken together, these results suggest that the bias in the merged sample does not vary systematically across treatment groups and therefore is unlikely to bias the estimated policy effects.

Raw DID Pre-Trend Analysis. At last, before presenting the main results, I assess the plausibility of the parallel-trends assumption underlying the raw difference-in-differences (DID) framework. Particularly, I estimate the event-study version of the equation (1) for treated cities without adding SDID weight. I plot the time trend of key outcomes in Figure C2, which do not have a significant difference before the policy implementation. This supports the use of a DID-type design and indicates that any bias from differential pre-trends is likely limited. Nonetheless, to further address the selection issue, I implement the SDID estimator as the main empirical specification, and report raw DID estimates in Section 5.5 as a robustness check.

5 Results on Treated and Neighboring Cities

5.1 Effect of Reallocation on Neighboring Cities

I begin by examining whether the KCAPC policy induced spatial reallocation in pollution-intensive production across city borders. The key empirical implication of the Pollution Haven Effect (PHE) in my setting is that regulatory stringency in treated cities leads to a shift of pollution-intensive production to less-regulated areas nearby. Establishing this pattern is critical to understanding whether the KCAPC generated reallocation rather than pure abatement.

This analysis focuses on non-treated cities that share a border with treated ones. Panel A of Table 6 presents the results, and the corresponding event-study plot in Figure 6 shows no significant pre-trends, supporting the validity of the comparison. Compared with distant control cities, neighboring cities experienced a statistically significant 20.7 percent[11] increase in total SO_2 emissions, a 16.2 percent increase in output, and a 12 percent gain in capital stock. Columns 1, 2, and 5 show that this growth in emissions was driven primarily by higher output rather than increased pollution intensity.

Panel B disaggregates these results by sectoral pollution intensity. The largest changes occur within the top-quintile polluting sectors. Column 5 shows that the increase in total output is concentrated among these pollution-intensive industries. Unlike the extensive-margin expansion seen later in treated cities, this growth appears to occur along the intensive margin: the number of firms changes little, while both output and capital stock increase substantially. Column 7 shows a similar pattern for capital stock accumulation.

Sector-specific estimates further reinforce this finding. In less-polluting sectors, the number of firms rose by 6.7 percent, output by 6.8 percent, and capital stock declined slightly (by 1.8 percent). In contrast, top-quintile polluting sectors saw a 10.9 percent increase in

[11] For log-transformed outcomes, percent changes are computed as $100 \times (\exp(\hat{\beta}) - 1)$. In this case, $\hat{\beta} = 0.188$, implying a 20.7 percent increase in SO_2 emissions. The same calculation applies throughout the discussion.

firm count, a 22.7 percent rise in output, and a 24.9 percent gain in capital stock. Although not all coefficients are statistically significant, the direction and magnitude of these effects consistently indicate that neighboring cities increasingly specialized in pollution-intensive activities following the policy's introduction.

However, column 1 shows no statistically significant difference in total SO_2 emissions between polluting and less-polluting sectors, which may reflect two offsetting effects: expansion of output in cleaner sectors and modest declines in emission intensity among polluting sectors. This interpretation is supported by Columns 1 and 5. Together, these results provide direct evidence consistent with a Pollution Haven Effect operating across city borders.

Having established that pollution-intensive activity expanded in neighboring cities, I next examine what happened in the regulated (treated) cities themselves.

5.2 Effect of KCAPC on Targeted Cities

Having documented reallocation to neighboring cities, I now turn to the direct effects of the KCAPC policy on the targeted, regulated cities. This analysis reveals whether the policy succeeded in reducing pollution in treated cities and whether it triggered structural adjustments within their industrial composition.

To assess dynamic treatment effects and check for pre-trends, I estimate the event-study version of Equation (1). The resulting point estimates are plotted in Figure 7. The coefficients show no statistically significant pre-trends prior to the policy's implementation in 2002, supporting the credibility of the identification strategy. Post-treatment effects do not reveal a consistent or significant decline in either economic activity or environmental outcomes. In particular, there is no clear downward trend in total SO_2 emissions or economic indicators following the policy.

Panel A of Table 7 reports the average treatment effects at the city level. The coefficients on SO_2 emissions and emission intensity per unit of output are negative, but none are statistically significant. In contrast, Columns 4 through 7 indicate that the policy is associated with a statistically significant 13.4 percent increase in total output, driven mainly by a 19.5 percent increase in the number of firms. This suggests that the average firm size declined, implying that the policy may have encouraged the entry of smaller firms, as aggregate pollution did not fall. This result is somewhat surprising, as the policy was designed to curb pollution, yet it results in an expansion of manufacturing activity in treated cities.

To understand these patterns, I estimate the heterogeneous effects using Equation (2), which distinguishes between polluting and less-polluting sectors. Panel B of Table 7 presents the results. Column 1 shows that emission intensity in polluting sectors declined by 18.9 percent, while less-polluting sectors saw a small and statistically insignificant increase. Column 2 indicates that SO_2 generation per unit of output fell by 16.4 percent, implying that about 86.8 percent of the observed reduction came from cleaner production processes rather than end-of-pipe abatement.

Column 3 shows that total SO_2 emissions in polluting sectors fell by 10.7 percent, while those in less-polluting sectors increased by 55 percent. Given that top-quintile polluting sectors accounted for 73.3 percent of baseline emissions, the implied overall change corresponds to a 6.8 percent increase in aggregate emissions—slightly smaller than the direct city-level estimate.

The increase in emissions from less-polluting sectors appears driven by output expansion, as shown in Column 5. However, output in these sectors rose by only 15.3 percent, compared to a 55 percent increase in emissions. This suggests that the additional production was significantly more pollution-intensive than before. This raises an important question: why do emissions rise in cleaner sectors, despite regulation targeting polluting sectors? As I will show in Section 6.1, this pattern is likely explained by firms in polluting sectors shifting toward less pollution-intensive product lines.

For polluting sectors, Columns 4 through 7 suggest more modest economic effects. Output increased by 7.8 percent, and the number of firms rose by 19.6 percent. This further supports the fact that firms in polluting sectors are now smaller. Although these effects are smaller in magnitude than those for less-polluting sectors, they are still positive and not statistically significant. Together, these findings suggest that the KCAPC policy did not result in an absolute contraction of polluting industries, but rather altered their relative growth patterns across sectors.

Overall, the results suggest that at the city level, the KCAPC policy primarily affected top-quintile polluting sectors and led to a shift in the source of emissions from these highly polluting industries toward relatively cleaner sectors. In terms of economic outcomes, I find that output grew significantly in less-polluting sectors, while growth in polluting sectors was more modest. However, although the coefficients for triple-difference indicators are negative, they are all insignificant, which is not strong enough to conclude that the policy induced a meaningful shift in economic specialization across sectors. Taken together, these results imply that there was a shift in pollution composition rather than economic specialization.

These findings differ from prior firm-level studies of the KCAPC policy, such as Liu et al. (2021) and Viard et al. (2022), which report significant reductions in firm-level emissions. Two factors may explain this divergence. First, my analysis focuses on sector-level aggregates, while their estimates are at the firm level, potentially capturing different aspects of the policy's effect. Second, the research designs differ in the construction of control groups. In particular, both of these studies rely on control observations from neighboring cities, either through propensity score matching (Liu et al., 2021) or geographic proximity (Viard et al., 2022), which are likely to have been affected by pollution spillovers. If treated cities shifted production to nearby areas, then using these cities as controls would bias estimated treatment effects downward. In the next section, I test this manifestation of the PHE directly and find evidence supporting my research design.

5.3 Location Quotient Analysis

The treated and neighbor results suggest that the KCAPC policy reshaped the sectoral composition of output and emissions in ways consistent with the PHE. To further validate this interpretation, I examine changes in regional industrial specialization using the Location Quotient (LQ) index. The LQ is a standard measure of relative specialization in agglomeration literature, defined as the ratio of a sector's share of activity in a city to its share at the national level.[12] An LQ above one indicates that a city is more specialized in that sector than the national average, while an LQ below one indicates less specialization.

While LQ provides an intuitive measure of specialization, absolute changes in LQ are not directly comparable across outcomes (firms, output, employment, capital) or over time. A shift of 0.1 in LQ may represent a meaningful change in one context but be negligible in another, depending on baseline variation. To facilitate comparability of effects across outcomes, I standardize the index within each year and sector to obtain a z-score measure (zLQ).[13] This rescaling expresses treatment effects in units of standard deviations relative to contemporaneous cross-city variation.

Restricting my analysis to the top quintile polluting sectors only, I estimate the following equation:

$$zLQ_{ct} = \alpha + \beta_1 \mathbb{1}\{W_c\} \times Post_t + \sigma_c + \tau_t + \epsilon_{ct} \tag{4}$$

Where zLQ_{ct} are standardized LQ for polluting sectors in targeted cities, and $\mathbb{1}\{W_c\}$ are either a dummy for the second round KCAPC cities or their respective non-treated neighbors.

I plot the coefficients as well as their respective 90% and 95% confidence intervals in Figure 8. The results show that treated cities experience a relative decline in LQ for polluting sectors, whereas neighboring cities see an increase, consistent with PHE. This additional evidence reinforces the baseline findings and complements the sector-level regression analysis.

[12] LQ has the following form: $LQ_{rs} = \frac{N_{rs}/N_r}{N_s/N}$, where N_{rs} is the number of firms (or output, employment, or capital) in sector s and city r, N_r is the total in city r, N_s is the total in sector s, and N is the overall total across all cities and sectors.

[13] $zLQ = \frac{LQ - LQ_{mean}}{LQ_{sd}}$

5.4 Discussion

In summary, the evidence from both treated cities and their neighboring regions suggests that the KCAPC policy primarily targets and affects top-quintile polluting sectors, but its overall effectiveness is limited. While the policy reduces both total SO_2 emissions and emission intensity within polluting sectors of treated cities, the net city-level effect on emissions is positive, albeit statistically insignificant. At the same time, neighboring cities experience a significant increase in emissions driven by growth in polluting sectors.

Overall, these findings provide empirical support for the Pollution Haven Effect at the regional level. First, in treated cities, there is a clear shift in the composition of pollution from high- to low-intensity sectors. Second, in neighboring cities, the increase in output is largely concentrated in pollution-intensive sectors. Third, within treated cities, the KCAPC policy appears to stimulate greater expansion in less-polluting sectors.

In the next section, I investigate the underlying mechanisms that may be driving these observed patterns of adjustment across regions and sectors.

5.5 Robustness Check

To further validate the results of the previous sections, I estimate my model with different settings as a robustness check.

5.5.1 Other Pollutant

First, I check the effect of the KCAPC policy on water pollution instead. China started various environmental regulation programs during my study period. Hence, it is possible that KCAPC coincides with other programs that target another source of pollution, i.e., water pollution. To verify that KCAPC policy's SO_2 regulation indeed drives the results, I estimate the policy effect on chemical oxygen demand (COD)[14] in Table B2 as a robustness

[14]COD measures the total amount of oxygen required to chemically oxidize organic and inorganic compounds in water, which is a common indicator for water pollution

check. The coefficients are all small and insignificant. The absence of similar patterns for COD confirms that observed shifts are pollutant-specific to SO_2 regulation.

5.5.2 Randomly Assigned Treatments

To ensure that the results are not driven by the use of the SDID model or by particular city–sector assignments, I conduct two placebo exercises by randomly assigning treatment status. First, I randomly select 65 cities[15] as treated 250 times and re-estimate the SDID specification. Figure C3 plots the distribution of $\hat{\beta}_3$ ($\mathbb{1}\{T_c\} \times Post \times Pol$) across these simulations. If the KCAPC policy truly drives the observed effects, the placebo distributions should be centered around zero, with no systematic negative effects for "treated" cities or positive effects for their neighbors. Consistent with this expectation, the simulated mean distributions are all close to zero and differ markedly from the baseline estimates. The only exception is a larger dispersion for total SO_2 emissions, likely reflecting the bias of the merged dataset toward large polluting firms. Importantly, the significant baseline coefficients fall in the tails of the simulated distributions, providing evidence that the main results are not artifacts of model choice or idiosyncratic city selection.

Applying the same approach, I randomly designate 61 sectors[16] as "treated" polluting sectors 250 times and re-estimate the SDID specification. Figure C4 shows the resulting distribution of $\hat{\beta}_3$. As expected, the simulated mean coefficients are centered around zero or display signs opposite to the baseline estimates. In contrast, the significant baseline coefficients lie in the tails of the placebo distributions, reinforcing the conclusion that the observed effects reflect heterogeneity between pollution-intensive and less-polluting sectors.

5.5.3 Outliers

A remaining concern is that the results could be driven by a few influential cities or sectors. Although first-round KCAPC cities (mostly provincial capitals and special economic zones)

[15] Consistent with the actual number of treated cities after excluding three western provinces.

[16] This number matches the actual count of top-quintile polluting sectors out of 308.

are excluded, some second-round cities or particular sectors might still exert disproportionate influence. I therefore implement leave-one-out (LOO) checks.

First, I drop one treated city at a time, and re-estimate the sectoral SDID specification, collecting the distribution of $\hat{\beta}_3$. I repeat the exercise for the neighboring-city analysis by dropping one neighbor at a time. If the baseline estimates are not driven by outliers, the LOO distributions should remain negative for treated cities and positive for neighbors.

Figure C5 shows that the treated-city LOO distributions are tightly centered on the baseline coefficients with limited dispersion. $\hat{\beta}_3$ remains negative throughout. The corresponding neighbor LOO distributions (Figure b) are also centered on the baseline. These patterns indicate that no single city drives the main results.

Second, I perform an analogous LOO exercise at the sector level, dropping one of the 61 top-quintile sectors in turn and re-estimating the model. Figure C6 shows that the LOO distributions are again centered close to the baseline coefficients. One notable dispersion appears for the total SO_2 emissions when excluding steelmaking. This is unsurprising given its size and pollution intensity. Even in that case, the estimated effect remains large and negative (around - 0.3), while the pollution-intensity results are stable and much less dispersed.

Overall, the LOO evidence indicates that the baseline findings are not driven by a small set of influential cities or sectors.

5.5.4 Model Specification

Additionally, to verify that the results are not driven by unobserved industry-specific trends over time, I re-estimate the SDID model including both city–sector and sector–year fixed effects. The results for treated and neighboring cities are reported in Table B4 and Table B3, respectively. Compared with the baseline estimates, adding sector–year fixed effects instead of year fixed effects has little impact on the magnitude or statistical significance of the coefficients. This robustness suggests that differential sectoral trends are unlikely to explain the main findings. One possible interpretation, consistent with Gibson (2019), is that abatement responses are largely discrete — reflecting one-time adjustments that stabilize thereafter — rather than persistent trends across industries.

5.5.5 Raw DID estimates

Finally, I also estimate the policy effects using a conventional DID model without synthetic weighting. The results are reported in Table B6 and Table B5, which are consistent in both magnitude and sign with the SDID estimates, reinforcing that the findings are not sensitive to the choice of estimator.

6 Mechanisms

To better understand the mechanisms driving the patterns presented in the above section, I assess three channels: within-firm product adjustment, extensive-margin dynamics (entry and exit), and non-market forces (State-ownership). The evidence points primarily to the third channel.

6.1 Firms Switching Products

Existing literature has documented that firms adjust their product mix in response to changes in market conditions and policy incentives (Bernard et al., 2010). In the context of environmental regulation, Gibson (2019) show that firms substitute among pollution inputs (for example, from air to water emissions) when relative abatement costs change. Hence, it is plausible that firms mitigate regulatory pressure by shifting toward less pollution-intensive products or sectors, particularly when policies target specific industries.

I next examine whether such within-firm adjustments help explain the heterogeneous patterns observed above. Specifically, I document evidence that the KCAPC policy induced a reallocation of production toward less-polluting sectors within treated cities, but that this "switching" behavior does not drive the observed cross-city differences in production patterns.

While the ASIF dataset lacks detailed product-level information, it records each firm's principal 4-digit industry classification, defined by the National Bureau of Statistics as the firms' principal production category.[17] Using this information, I identify firms that change their 4-digit sector across years, treating such changes as switches in principal production activity. In particular, I focus on firms that move from a top-quintile polluting sector to a less-polluting one, hereafter switching firms. Although some reclassifications may reflect coding noise rather than real production changes, the patterns below suggest that any misclassification is limited and unlikely to bias the results.

Switching firms are concentrated in highly polluting industries and tend to change production within the same 2-digit division. Figure C7 shows that 2-digit sectors with the highest frequency of switches are also those with greater pollution intensity. Roughly 75 percent of switching firms remain within their original 2-digit sector, implying a move to less-polluting activities within the same industry. Examples include chemical producers shifting from basic to organic chemicals, textile firms moving from fiber processing to finished textiles, and non-metal mineral enterprises transitioning from cement to concrete products.

Switching behavior is also more prevalent in treated cities. Figure C8 reports the share of switching firms and their contributions to aggregate outcomes by treatment group. Two patterns emerge. First, switching firms are larger and more polluting on average, as reflected in their disproportionate shares of total output and SO_2 emissions relative to their population share. Second, treated cities exhibit a noticeably higher incidence of switching than neighboring or distant control cities. These patterns suggest that product switching is one channel through which firms adapt to sector-specific environmental regulation.

To examine this formally, I estimate two equations:

[17] According to the National Bureau of Statistics, a firm's principal activity is the one that contributes the largest share of its value added. See Statistical Systems and Classification Standards (17) (in Chinese).

$$Switch_{it} = \beta_1 \mathbb{1}\{T_i\} \times Post_t + \gamma X_{ct} + \sigma_i + \tau_t + \epsilon_{it} \tag{5}$$

$$ln(Y_{it}) = \beta_1 \mathbb{1}\{T_i\} \times Post_t \times Switch_{it} + \gamma X_{ct} + \sigma_i + \tau_t + \epsilon_{it} \tag{6}$$

Where i indexes the firm, c denotes the city, and t represents the year. The dependent variable in the first equation, $Switch_{it}$, is a binary indicator equal to one if a firm switches from a top-quintile polluting sector to a less-polluting sector in year t. The second specification examines the correlation between switching and firm-level outcomes. The key regressor is a triple interaction between KCAPC treatment, the post-treatment period, and the switching indicator. Y_{it} includes outcomes such as firm output, capital stock, and employment.

Table 8 presents the results. Column 1 shows that firms in treated cities are significantly more likely to switch to less-polluting sectors after the policy. Columns 2–4 indicate that, conditional on switching, these firms exhibit higher output and capital stock in the post-policy period. These findings suggest that switching serves as a proactive strategy allowing firms to sustain or even expand performance under regulatory constraints.

To assess whether such switching behavior explains the cross-city differences documented earlier, I re-estimate the baseline model after excluding all switching firms. Columns 1–2 of Table 9 compare the results for treated and neighboring cities with those based on the full sample. For consistency, switching in neighboring cities is symmetrically defined as firms moving from less- to more-polluting sectors. The coefficients remain virtually unchanged across specifications, indicating no meaningful differences for either treated or neighboring cities. Therefore, while product switching is indeed a response to KCAPC regulation, it does not account for the differential production patterns observed across cities.

6.2 Entry and Exit

Having examined within-firm adjustments, I turn to the extensive margin. Specifically, I study how the KCAPC affected entry and exit in treated and neighboring cities, which sheds light on whether location decisions reinforce or drive the observed changes in industrial composition. The evidence shows that entry–exit dynamics reinforce sectoral shifts but do not account for them.

Because ASIF covers only non-SOEs with annual sales above 5 million yuan, identifying true entrants requires care. I define a firm as an *entrant* in year t if it appears in the sample for the first time in t and: (i) its reported birth year is not before 1998 (the first sample year), and (ii) if it first appears after 2002, its reported birth year is not before 2002. These restrictions reduce false positives created by left-censoring and delayed inclusion. An *exiter* is a firm whose last observation occurs in year t; I censor the final sample year by excluding firms whose last observation is in 2007 to avoid conflating exit with sample termination.[18]

At the city–sector level, the entry rate (respectively, exit rate) is the fraction of entrants (exiters) in the total number of firms; net entry is the difference between the two. I estimate policy effects on these outcomes using the main city–sector specification and report the results in Table 10.

Panel A shows that, in treated cities, polluting sectors experience a statistically significant increase in the exit rate and a decline in net entry (Columns 1 and 3), consistent with some turnover away from pollution-intensive activities. Magnitudes are small, economically close to zero, and entry effects are weak, indicating that extensive-margin responses account for only a limited share of the overall adjustment. In neighboring cities (Panel B), the policy has no statistically discernible effects on entry, exit, or net entry.

Taken together, the extensive margin does not appear to be the primary channel through which KCAPC reshapes industrial composition. Rather, reallocation operates mainly along

[18] Results are robust to (i) requiring two consecutive years of presence for entrants, (ii) defining exit as no reappearance for two subsequent years, and (iii) additionally censoring 2006.

the intensive margin, through adjustments among incumbents (expansion of less-polluting producers and contraction in pollution intensity among polluting sectors). The next subsection shows that these incumbent adjustments are concentrated among SOEs.

6.3 State-Owned Enterprises and Non-SOEs

Finally, I examine whether the observed reallocation was driven by non-market forces. While prior studies find that structural reallocation typically unfolds gradually over long periods (Curtis et al., 2025), my results show substantial changes within just five years (2002–2007). Such rapid adjustment raises the possibility that the reallocation was facilitated by government intervention at the provincial level. In particular, I find that State-Owned Enterprises (SOEs)[19] absorbed most of the adjustment within treated cities and the increase in polluting activity in neighboring cities, suggesting their role as instruments of policy coordination across jurisdictions.

Local governments in developing countries often operate under weak institutional constraints or prioritize economic growth over regulation (Duflo et al., 2013; Jia, 2017; Du and Li, 2023). As a result, pollution-intensive firms tend to cluster near the borders of regulated jurisdictions to minimize enforcement (Lipscomb and Mobarak, 2016; Monogan III et al., 2017; Cai et al., 2016). This pattern is particularly salient in China, where provincial officials face top-down performance evaluations emphasizing GDP growth (Chang et al., 2025). This "top-down amplification" (Jia, 2017) can lead provinces to reallocate polluting activities to nearby, less-regulated cities within their borders to simultaneously satisfy environmental and growth targets.

SOEs are well-positioned to facilitate such political objectives for two reasons.

First, they represent a substantial share of the a city's industrial base, particularly in heavy and pollution-intensive sectors. Table B7 reports SOE shares in firm counts, output, and SO_2 emissions across all sectors, while Table B8 focuses on polluting sectors. Although

[19] I classify SOEs following Hsieh and Song (2015). A firm is identified as an SOE if it is explicitly state-controlled or if the share of registered capital held by the state equals or exceeds 50 percent.

treated cities began the period with similar SOE shares as other regions, their decline in SOE presence over time was noticeably slower. Moreover, within polluting sectors, SOEs accounted for a larger share and exhibited a sharper rate of decline, consistent with differential adjustment by ownership type.

Second, SOEs are expected to facilitate the provincial and city governments in fulfilling policy targets (Berkowitz et al., 2017). Provincial governments exert substantial control over SOEs, including managerial appointments, investment decisions, and privatization authority.[20] Figure C9 shows that treated cities maintained higher shares of non-privatized SOEs in 2007 in both output and emissions. These patterns suggest that city governments, under provincial oversight, relied on SOEs to buffer against the policy's economic costs.

To test this formally, I re-estimate the policy effects separately for SOEs and non-SOEs.[21] Results are presented in Columns 3–6 of Table 9.

In treated cities, SOEs are the main source of heterogeneity between polluting and less-polluting sectors. As shown in Column 4 of Panel A, output in less-polluting sectors expanded by 0.495, compared with a smaller increase of 0.207 in polluting sectors, a difference partly driven by changes in firm counts (Column 3). In contrast, for non-SOEs (Columns 5–6), coefficients are small, statistically insignificant, and similar across sector types. These results indicate that provincial and city governments leveraged SOEs to absorb regulatory pressure and maintain production stability. Based on coefficient magnitudes and output shares, SOEs account for approximately 78 percent[22] of the observed output increase in less-polluting sectors.

In neighboring cities (Panel B), the pattern reverses: SOEs exhibit pronounced growth in polluting sectors, while non-SOEs expand in both polluting and cleaner sectors. This asym-

[20]For official documentation, see Interim Regulation on the Supervision and Administration of State-owned Assets of Enterprises (2003) (in Chinese) and Measures for Guiding and Supervising the Regulation of Local State-owned Assets (2011) (in Chinese), as well as Hsieh and Song (2015) for discussion.

[21]SOEs are defined as all firms that were ever state-controlled during the sample period, given that former SOEs may retain close ties with local governments.

[22]The contribution of SOEs is calculated as $x = 1 - w \cdot \frac{\beta_{\text{soe}}}{\beta}$, where w is the output share of SOEs (22.5 percent), β_{soe} is the coefficient for $KCAPC \times Post$ in Column 4, Panel A, Table 9, and β is the corresponding coefficient in Column 5, Panel B, Table 7.

metry suggests that provincial coordination redistributed polluting activities from regulated to neighboring cities using SOEs.

Overall, the observed heterogeneous treatment effects between polluting and less-polluting sectors are largely driven by SOEs. The persistent presence of SOEs in treated cities, which is due to a slower rate of privatization compared to other regions, helps explain why non-SOEs were more likely to relocate, while SOEs remained to absorb regulatory shifts. Given their close ties to provincial authorities, SOEs serve as effective instruments for coordinating industrial policy across jurisdictional boundaries.

Beyond direct political mandates, an additional economic mechanism reinforces this pattern. Provincial governments can channel preferential financing and investment opportunities toward SOEs, lowering their effective cost of capital and enabling expansion in targeted sectors. Consistent with this, Berkowitz et al. (2017) documents rising capital intensity among SOEs during this period. My findings in Table B9 further support this: SOEs in treated cities significantly increased capital stock in less-polluting sectors, while their counterparts in neighboring unregulated regions expanded most aggressively in polluting industries. This sector-specific investment behavior underscores that both political and economic incentives shaped the strategic use of SOEs in mediating the effects of environmental regulation.

The rapid and symmetric nature of this adjustment suggests that the mechanism operates through provincial-level coordination rather than city-level market forces. To test this, I perform a falsification exercise by estimating the policy's effect on cross-province neighbor cities, i.e., those that share a border with a treated city but reside in a different province. The results in Table B10 show that the triple-difference coefficients for these cities are mostly small and statistically insignificant. If the reallocation were driven by city-level competition or general geographic spillovers, we would expect to see similar effects regardless of provincial borders. The absence of an effect in cross-province neighbors suggests that the "pollution haven" response is contained within provincial jurisdictions, pointing to the province as the primary unit of coordination.

Two additional observations reinforce this provincial-coordination hypothesis. First, if unregulated cities were independently competing to attract "dirty" production, we would expect high variance in outcomes across neighbors (i.e., "winning" and "losing" cities). Second, market-driven relocation would likely be more pronounced among profit-seeking non-SOEs. Instead, the dominant and systematic role of SOEs confirms that provincial governments strategically use these enterprises to mitigate the economic costs of environmental regulation while maintaining formal policy compliance.

Together, the findings are consistent with the view that provincial governments strategically used SOEs to absorb regulatory pressure, aided by city-level facilitation: by expanding SOEs' presence in less-polluting sectors within treated cities and in polluting sectors within neighboring cities, provincial governments mitigated the economic costs of environmental regulation while formally complying with policy mandates.

6.4 Discussion

Across the three channels, the evidence points to a common mechanism. First, within-firm product switching is more prevalent in treated cities and is economically meaningful for those firms, but excluding all switchers leaves the city-level results unchanged, indicating that switching does not account for cross-city reallocation. Second, entry–exit responses are statistically detectable only in treated polluting sectors (higher exit, lower net entry) and are small in magnitude, implying that the extensive margin reinforces but does not drive aggregate patterns. Third, ownership heterogeneity is decisive: SOEs absorb most of the adjustment in treated cities' less-polluting sectors and expand in polluting sectors of neighboring cities. Calculations indicate that SOEs account for roughly 78% of the observed increase in output in less-polluting sectors within treated areas.

To sum up, these facts are consistent with a provincial coordination mechanism, implemented through SOEs and facilitated by city governments: provinces reallocate pollution-intensive activity from regulated to neighboring cities while preserving production in treated areas by shifting SOE capacity toward cleaner sectors. This mechanism reconciles the absence of large aggregate contractions in treated cities with the documented rise in pollution and output next door, thereby providing a concrete channel for the Pollution Haven Effect within China's administrative hierarchy.

7 Conclusion

Can city-specific environmental regulation induce Pollution Haven–style reallocation, and through which mechanisms do such effects operate? To address these questions, this paper examines China's Key Cities Air Pollution Control (KCAPC) program, which is a national policy that imposed stricter emission controls on pollution-intensive sectors in selected cities, and evaluates its environmental and economic consequences. I analyze both aggregate outcomes (total emissions and pollution intensity) at the city level and sectoral responses in output, capital, and employment.

Using a synthetic difference-in-differences approach to construct credible counterfactuals, I document evidence consistent with a within-country Pollution Haven Effect: The KCAPC policy significantly reduces pollution intensity only among the most pollution-intensive (top-quintile) sectors in treated cities. At the same time, treated cities shift production toward cleaner sectors, while neighboring non-regulated cities expand output and capital in pollution-intensive sectors.

Further analysis points to two mechanisms behind these patterns. First, provincial governments strategically reallocate production through state-owned enterprises, which expand in cleaner sectors within regulated cities and in more polluting sectors in neighboring ones. Second, some firms adjust within cities by shifting their principal products toward less pollution-intensive activities. Together, these results suggest that policy-induced reallocation is primarily coordinated through political rather than purely market channels.

Overall, the findings underscore that environmental regulation implemented at a lower administrative level can displace emissions to adjacent jurisdictions. The effectiveness of such policies therefore depends on whether the *unit of regulation* aligns with the *unit of coordination* for economic activity and enforcement. Designing policy to match these units, and to anticipate inter-jurisdictional spillovers, can improve both environmental effectiveness and distributional outcomes.

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Tables

Table 1: Annual Statistics of Original and Merged Datasets

	N (Firms, thousand)		GVO (trillion RMB)		SO2 Emission (million ton)	
Year	ASIF	Merged (%)	ASIF	Merged (%)	AESPF	Merged (%)
1998	133.5	15.9	5.8	30.9	13.6	36.4
1999	132.7	19.2	6.2	38.0	11.4	26.5
2000	135.2	20.2	7.3	39.8	12.7	25.6
2001	145.6	18.9	8.2	39.0	13.5	24.2
2002	154.9	18.0	9.6	39.8	13.3	24.8
2003	173.2	16.6	12.6	37.7	14.9	24.4
2004	244.7	13.7	17.2	37.1	17.3	25.6
2005	241.7	13.9	21.3	38.9	19.9	24.9
2006	269.9	13.6	26.8	39.2	20.6	23.6
2007	304.3	15.5	34.7	41.5	19.5	26.7

Notes: N is the total number of firms (thousand), GVO is gross value of output (trillion RMB), and SO_2 Emission is sulfur dioxide emissions (million tons). For each variable, the column labeled "Merged (%)" reports the share of the variable successfully matched into the merged dataset relative to the corresponding total in the original dataset (ASIF for firms and GVO, AESPF for SO_2). For example, in 1998 the merged dataset contains 15.9% of the firms recorded in ASIF.

Table 2: Pollution Intensity by Sector (Ranked by SO_2/GVO)

Sector Name	SO_2/GVO	Fraction Firms (ASIF)	Fraction Firms (Merged)
Non-Metal Minerals	8.10	8.58	16.03
Non-Ferrous Metals	7.63	1.93	2.69
Petroleum Processing	6.08	0.72	1.29
Paper Products	4.19	2.98	5.38
Chemical Products	3.96	7.49	12.46
Wood Processing	2.83	2.02	1.16
Ferrous Metals	2.20	2.33	3.67
Beverage	2.16	1.75	3.33
Textile	1.76	8.46	9.57
Food Manufacturing	1.53	2.57	3.73
Chemical Fiber	1.46	0.53	0.54
Rubber Products	1.38	1.18	1.13
Pharmaceuticals	1.17	2.04	4.24
Food Processing	1.14	6.29	6.31
Special Equipment	0.89	4.18	2.46
Electronics	0.81	2.04	1.33
Plastic Products	0.80	4.60	1.63
Clothing	0.77	4.83	1.35
Tobacco	0.77	0.13	0.38
Instruments	0.74	1.77	1.16
Other	0.73	1.06	0.66
Transport Equipment	0.69	4.54	3.51
Printing	0.60	2.10	0.88
Leather Products	0.60	2.37	1.42
Furniture	0.59	1.16	0.34
General Machinery	0.58	7.38	4.58
Metal Products	0.55	5.62	3.87
Cultural Goods	0.48	1.31	0.46
Electrical Equipment	0.27	4.19	2.85

Notes: This table lists 2-digit sectors ranked by SO_2 emission intensity (SO_2/GVO, kg / thousand yuan). Columns 3 and 4 report the fraction of firms a sector accounts for in the ASIF and Merged datasets. The horizontal line separates sectors: those above the line are mentioned in the Five-Year Plan (except the wood processing sector).

Table 3: Effect on Sectors by Pollution Intensity Quintiles

VARIABLES	(1) ln(SO2e/Out)	(2) ln(SO2e/Out)
$\mathbb{1}\{T\} \times$ Post	0.137	
	(0.481)	
$\mathbb{1}\{T\} \times$ Post $\times$ Q2	-0.173	-0.184
	(0.449)	(0.434)
$\mathbb{1}\{T\} \times$ Post $\times$ Q3	-0.333	-0.340
	(0.161)	(0.161)
$\mathbb{1}\{T\} \times$ Post $\times$ Q4	-0.095	-0.149
	(0.693)	(0.537)
$\mathbb{1}\{T\} \times$ Post $\times$ Q5	-0.408*	-0.403*
	(0.065)	(0.068)
City FE	Y	
City-Year FE		Y
Sector-Year FE	Y	Y
Observations	4,573	4,560
R-squared	0.563	0.668

Notes: p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the city level. Qn represent nth quntile in terms of sectoral pollution intensity.

Table 4: Variable Definitions

Variable Name	**Definition**
$\mathbb{1}\{T\}$	A dummy that equals 1 for second round KCAPC cities
$\mathbb{1}\{N\}$	A dummy that equals 1 for cities neighboring a 2nd round KCAPC cities
Pol	A dummy that equals 1 for top quintile polluting sectors
Post	A dummy that equals 1 for year 2002 and onward
SO2e_{tot}	Total sulfur oxide (SO_2) emission
SO2e/Out	Average firm-level SO_2 emission intensity (firm total emission over total output)
SO2g/Out	Average firm-level SO_2 generation intensity (firm total pollution generated over total output)
Nfirms	Total number of firms
Output	Total firm output (in thousand yuan)
Emp	Total number of firm employment
Cap	Total firm captical stock (in thousand yuan)

Table 5: Summary Statistics

Variable	(1) Control			(2) Neighbor			(3) Treated		
	N	$\frac{\text{Mean}}{\text{SD}}$	Top 20%	N	$\frac{\text{Mean}}{\text{SD}}$	Top 20%	N	$\frac{\text{Mean}}{\text{SD}}$	Top 20%
SO2 Emission	667	6.3	76.3	1,252	8.3	74.7	640	17.1	73.3
		(10.5)			(9.2)			(19.5)	
SO2 Generation	667	11.3	76.9	1,252	16.9	75.7	640	26.1	73.2
		(34.6)			(44.9)			(31.6)	
Number of Firms	690	323.0	28.9	1,280	315.2	32.8	650	579.4	31.3
		(629.6)			(489.4)			(805.9)	
Output	690	25.1	39.3	1,280	21.3	40.6	650	54.6	39.8
		(66.1)			(34.5)			(87.2)	
Employment	690	89.8	41.4	1,280	78.7	44.3	650	171.1	43.4
		(198.4)			(90.7)			(167.9)	
Capital Stock	690	7.1	48.6	1,280	6.8	51.2	650	18.4	49.8
		(13.6)			(7.9)			(19.1)	
Export	690	5.8	–	1,280	2.4	–	650	5.7	–
		(22.9)			(8.8)			(14.3)	
Mean wage	690	10.5	–	1,280	9.9	–	650	10.6	–
		(4.5)			(4.6)			(4.5)	
Population	690	2,791.5	–	1,280	3,725.3	–	650	4,165.0	–
		(2,010.5)			(2,079.5)			(2,165.2)	

Notes: The observations (N) here are aggregated at the city level. Emission and economic outcomes have a different number of observations because some city-years observations do not have matched SO_2 outcomes. Standard deviations are reported in parentheses. All SO_2 outcomes are in thousand tons. All monetary values are in billion RMB, except the mean wage is in thousand RMB. Employment and population are in thousands. In "Top 20%" column, I report the percentage of the total contributed by top quintile polluting sectors.

Table 6: Effects of KCAPC on Neighboring Cities

	SO2 Outcomes			Economic Outcomes			
	(1) ln(SO2e/Out)	(2) ln(SO2g/Out)	(3) ln($SO2e_{tot}$)	(4) ln(Nfirms)	(5) ln(Output)	(6) ln(Emp)	(7) ln(Cap)
Panel A. Aggregate Effects							
$\mathbb{1}\{N\} \times$ Post	0.000	-0.016	0.188*	0.092	0.150**	0.014	0.113**
	(0.999)	(0.851)	(0.067)	(0.106)	(0.011)	(0.782)	(0.030)
City FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,558	1,558	1,907	1,950	1,755	1,950	1,755
R-squared	0.754	0.760	0.799	0.947	0.967	0.969	0.961
Panel B. Heterogeneous Effects							
$\mathbb{1}\{N\} \times$ Post	0.013	0.003	0.158	0.065	0.066	-0.035	-0.018
	(0.907)	(0.977)	(0.278)	(0.303)	(0.381)	(0.541)	(0.782)
Pol $\times$ Post	0.272***	0.282***	0.097	-0.008	-0.263***	-0.229***	-0.271***
	(0.006)	(0.006)	(0.429)	(0.791)	(0.000)	(0.000)	(0.000)
$\mathbb{1}\{N\} \times$ Post $\times$ Pol	-0.051	-0.055	-0.006	0.038	0.138*	0.079	0.240***
	(0.683)	(0.665)	(0.968)	(0.334)	(0.093)	(0.113)	(0.001)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.038	-0.052	0.152	0.103	0.204	0.044	0.222
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	3,090	3,091	3,778	3,900	3,510	3,900	3,510
R-squared	0.798	0.806	0.798	0.948	0.951	0.959	0.939

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $\hat{\beta}_1$ represent $\mathbb{1}\{N\} \times$ Post and $\hat{\beta}_3$ represent $\mathbb{1}\{N\} \times$ Post $\times$ Pol. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table 7: Effects of KCAPC on Treated Cities

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln(SO2e/Out)	ln(SO2g/Out)	ln($SO2e_{tot}$)	ln(Nfirms)	ln(Output)	ln(Emp)	ln(Cap)
Panel A. Aggregate Effects							
$\mathbb{1}\{T\}$ × Post	-0.083	-0.058	0.098	0.178***	0.126**	-0.016	0.068
	(0.425)	(0.576)	(0.417)	(0.003)	(0.031)	(0.741)	(0.184)
City FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,054	1,054	1,295	1,320	1,188	1,320	1,188
R-squared	0.718	0.723	0.828	0.965	0.979	0.982	0.979
Panel B. Heterogeneous Effects							
$\mathbb{1}\{T\}$ × Post	0.087	0.109	0.441**	0.181***	0.142*	0.002	0.125
	(0.500)	(0.396)	(0.017)	(0.006)	(0.073)	(0.974)	(0.135)
Pol × Post	0.253**	0.254**	-0.024	-0.011	-0.300***	-0.242***	-0.311***
	(0.045)	(0.047)	(0.873)	(0.719)	(0.000)	(0.000)	(0.000)
$\mathbb{1}\{T\}$ × Post × Pol	-0.297**	-0.288*	-0.554**	-0.024	-0.067	-0.071	-0.089
	(0.045)	(0.053)	(0.014)	(0.562)	(0.559)	(0.356)	(0.505)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.210	-0.179	-0.113	0.157	0.075	-0.069	0.036
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	2,089	2,089	2,563	2,640	2,376	2,640	2,376
R-squared	0.798	0.806	0.792	0.967	0.961	0.970	0.948

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the city level. $\hat{\beta}_1$ represent $\mathbb{1}\{T\}$ × Post and $\hat{\beta}_3$ represent $\mathbb{1}\{T\}$ × Post × Pol. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table 8: Results for Firms Switching Products

VARIABLES	(1) Switch	(2) ln(Output)	(3) ln(Emp)	(4) ln(Cap)
$\mathbb{1}\{T\} \times$ Post	0.003**			
	(0.030)			
$\mathbb{1}\{T\} \times$ Post $\times$ Switch		0.067***	0.011	0.104***
		(0.000)	(0.520)	(0.000)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	565,226	564,951	565,226	565,226
R-squared	0.192	0.866	0.897	0.919

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the city level.

Table 9: Heterogeneous Effects by Firm Type and Region

	Non-switching Firms		SOEs		Non-SOEs	
	(1) ln(Nfirms)	(2) ln(Output)	(3) ln(Nfirms)	(4) ln(Output)	(5) ln(Nfirms)	(6) ln(Output)
Panel A. Treated Cities						
$\mathbb{1}\{T\}$ × Post	0.185***	0.131*	0.307***	0.495***	0.023	0.020
	(0.006)	(0.066)	(0.000)	(0.000)	(0.751)	(0.818)
Pol × Post	0.032	-0.148**	0.245***	-0.224*	-0.047	0.009
	(0.295)	(0.019)	(0.000)	(0.053)	(0.253)	(0.913)
$\mathbb{1}\{T\}$ × Post × Pol	-0.017	-0.002	-0.195***	-0.288	0.012	0.072
	(0.679)	(0.982)	(0.000)	(0.109)	(0.823)	(0.522)
$\hat{\beta}_1 + \hat{\beta}_3$	0.168	0.129	0.112	0.207	0.035	0.092
Observations	2,640	2,376	2,064	2,580	2,520	2,268
R-squared	0.966	0.970	0.950	0.911	0.960	0.953
Panel B. Neighboring Cities						
$\mathbb{1}\{N\}$ × Post	0.063	0.095	0.052	0.050	0.113*	0.200**
	(0.320)	(0.216)	(0.362)	(0.597)	(0.089)	(0.024)
Pol × Post	-0.076**	-0.295***	0.242***	-0.188*	-0.054	0.038
	(0.011)	(0.000)	(0.000)	(0.062)	(0.168)	(0.625)
$\mathbb{1}\{N\}$ × Post × Pol	0.058	0.112	-0.049	0.176	-0.027	-0.001
	(0.144)	(0.180)	(0.332)	(0.137)	(0.611)	(0.989)
$\hat{\beta}_1 + \hat{\beta}_3$	0.121	0.207	0.003	0.226	0.086	0.199
Observations	3,510	3,510	3,040	3,800	3,760	3,384
R-squared	0.948	0.952	0.930	0.890	0.943	0.942
City-Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: P-values in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table 10: Effects on Exit, Entry, and Net Entry Rates

	(1) Exit Rate	(2) Entry Rate	(3) Net Entry
Panel A. Treated Cities			
$\mathbb{1}\{T\}$ × Post	-0.027**	-0.007	0.021
	(0.023)	(0.568)	(0.194)
Pol × Post	-0.013	-0.012	0.002
	(0.216)	(0.282)	(0.897)
$\mathbb{1}\{T\}$ × Post × Pol	0.026**	-0.002	-0.028*
	(0.039)	(0.869)	(0.100)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.001	-0.009	-0.009
Observations	2,112	2,376	2,112
R^2	0.330	0.642	0.510
City-Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel B. Neighboring Cities			
$\mathbb{1}\{N\}$ × Post	-0.017	-0.013	0.004
	(0.186)	(0.285)	(0.804)
Pol × Post	-0.014	-0.014	0.001
	(0.180)	(0.203)	(0.949)
$\mathbb{1}\{N\}$ × Post × Pol	0.012	0.009	-0.002
	(0.339)	(0.469)	(0.893)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.005	-0.004	0.002
Observations	3,120	3,510	3,120
R^2	0.306	0.626	0.500
City-Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined treatment effect for polluting sectors.

Figures

Figure 1: Map of KCAPC Cities

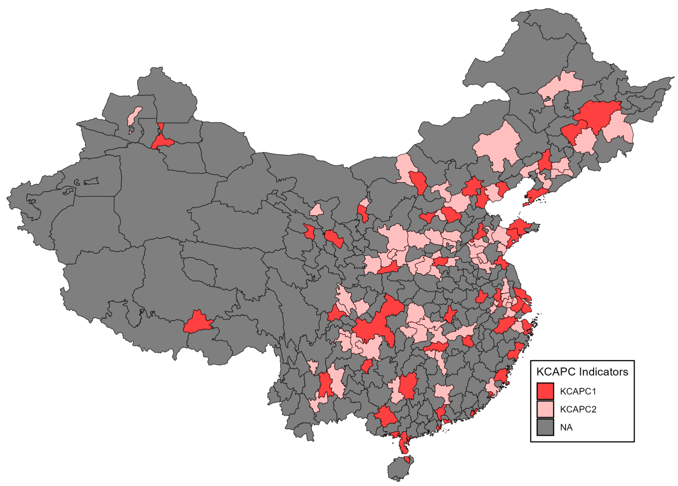
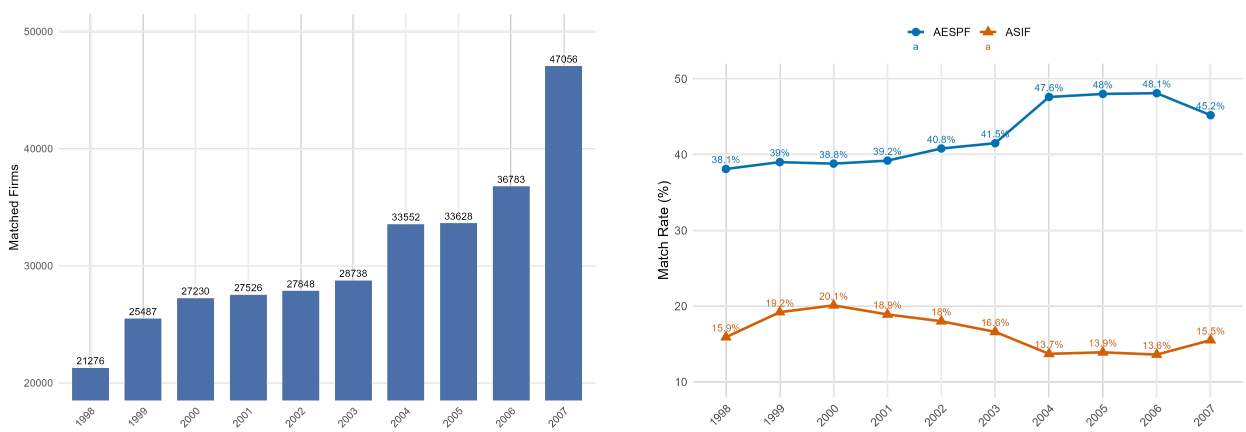


Figure 2: Merge results for ASIF and AESPF

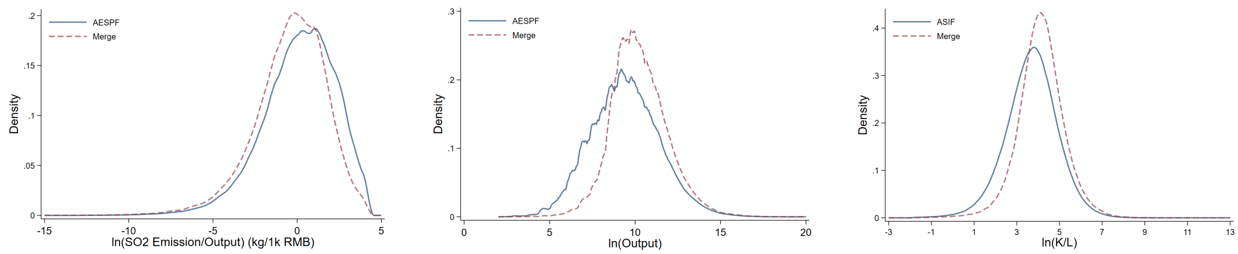


(a) Matched Firms (bar chart)

(b) Match Rates (ASIF vs AESPF)

Note: Panel (a) shows the total number of successfully matched firms each year from ASIF and AESPF datasets. Panel (b) compares match rates over time between ASIF and AESPF using line graphs.

Figure 3: Distribution of Key Stats Between Datasets



(a) Emission Intensity (b) Output (b) Capital Labor Ratio

Note: Panels (a) and (b) compare the firm-level distribution of SO_2 intensity / output between the merged and AESPF datasets. Panel (c) compares the firm-level real capital stock / employment between the merged and ASIF datasets.

Figure 4: Trends in Sectoral SO_2 Generation Intensity by Decile Bins (1998–2007)

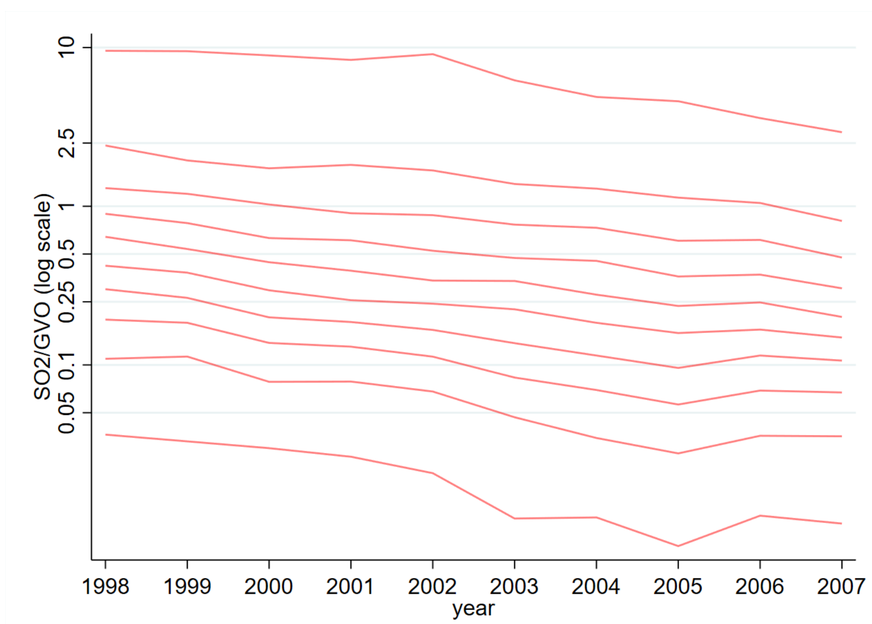


Figure 5: Map of Cities by Treatment Status

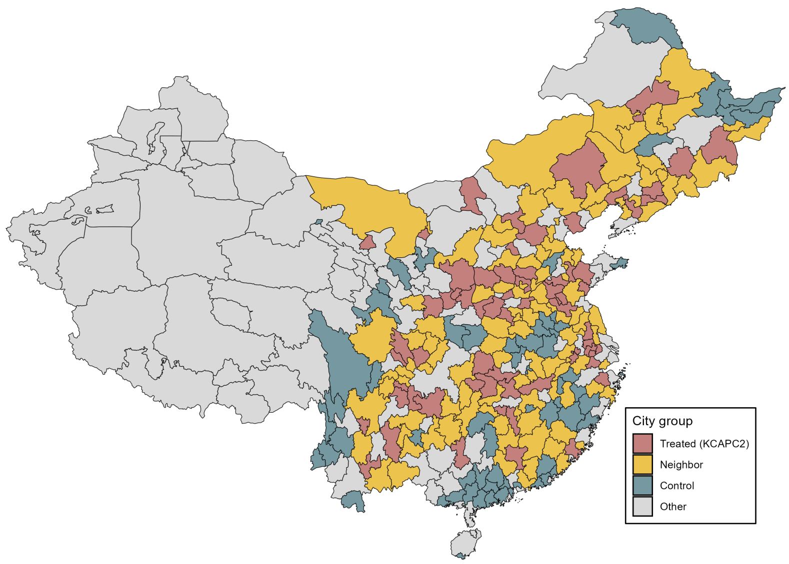
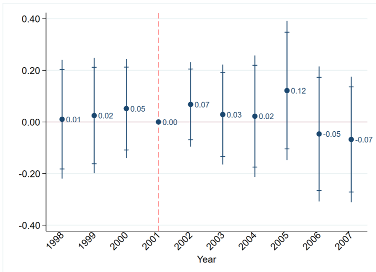
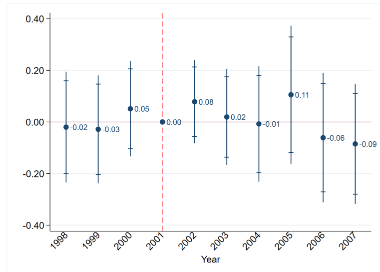


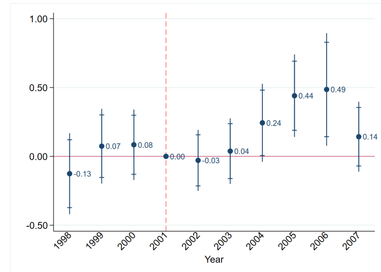
Figure 6: Pre-trend for Aggregate Effects in Neighbor Cities



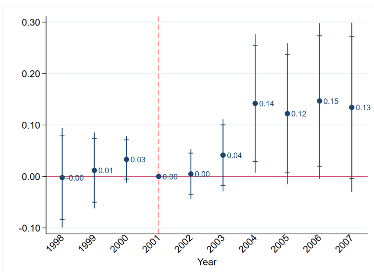
(a) SO_2 Emission Intensity



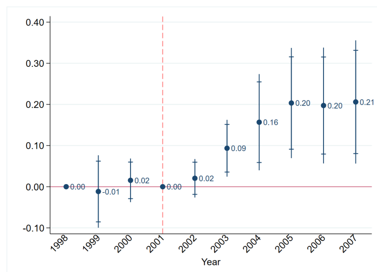
(b) SO_2 Generation Intensity



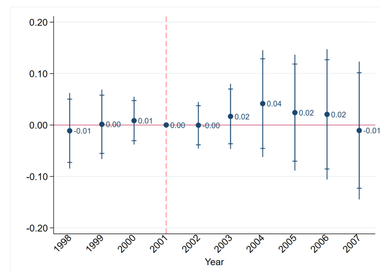
(c) Total SO_2 Emission



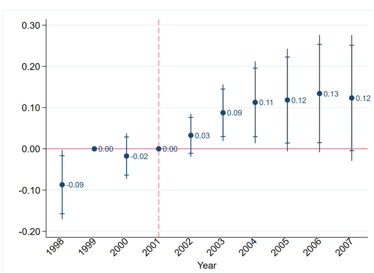
(d) Nfirms



(e) Output



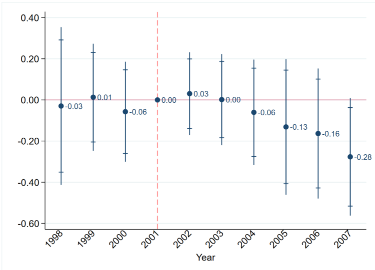
(f) Employment



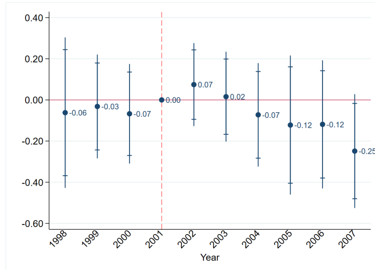
(g) Capital Stock

Note: One pre-trend year is missing for some variables (output and capital stocks) because that year receives zero weight in the SDID regression.

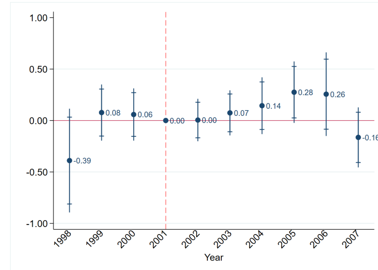
Figure 7: Pre-trend for Aggregate Effects in Treated Cities



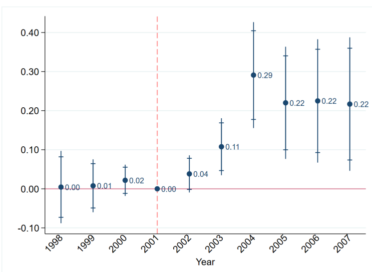
(a) SO_2 Emission Intensity



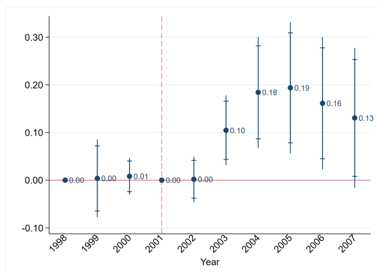
(b) SO_2 Generation Intensity



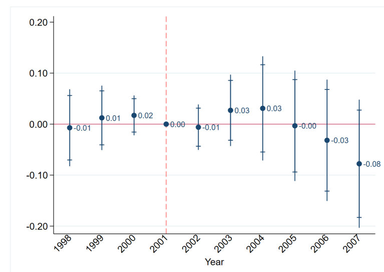
(c) Total SO_2 Emission



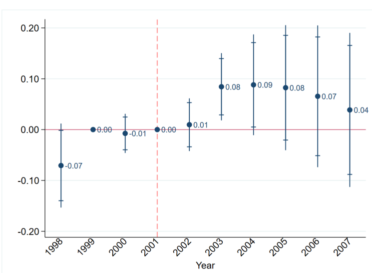
(d) Nfirms



(e) Output



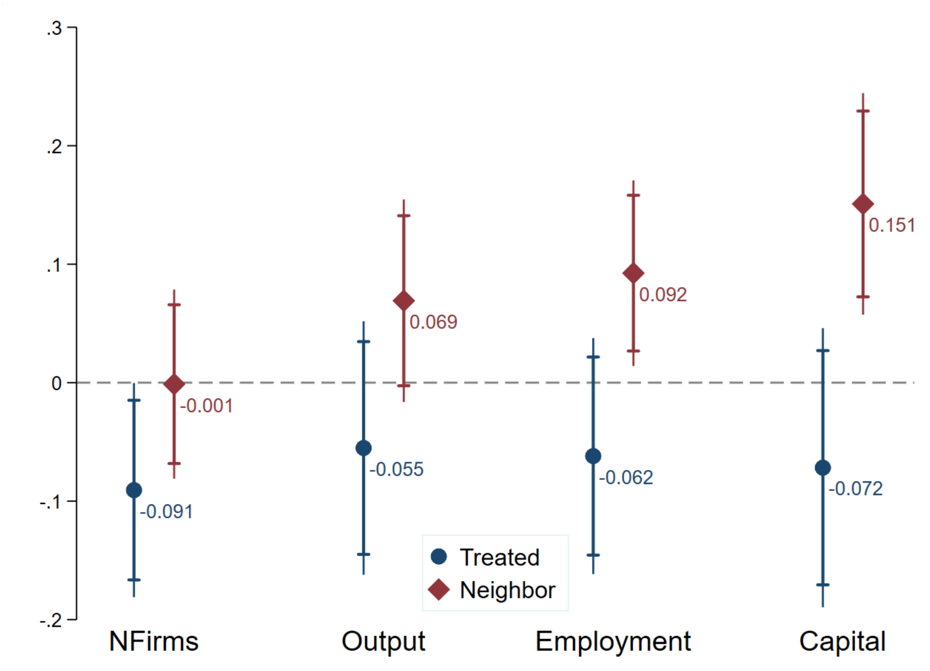
(f) Employment



(g) Capital Stock

Note: One pre-trend year is missing for some variables (output and capital stocks) because that year receives zero weight in the SDID regression.

Figure 8: Change in zLQ after 2002 for Treated and Neigbor Cities



Note: This figure plots point estimates and their confidence intervals (CIs) for the standardized location quotient index of polluting sectors across economic outcomes. The bars represent 90% CIs, while the spikes represent 95% CIs.

APPENDIX

A Calculate City and Year Weight using Synthetic Difference-in-Difference

As mentioned in the Section 2, the central government selects treated cities based on their overall development and pollution level. Therefore, using raw DID is unlikely to obtain unbiased results. To mitigate this concern, I use a synthetic difference-in-difference approach proposed by Arkhangelsky et al. (2021). In my setting, this method calculates an optimal city and year weight to construct a counterfactual control group whose time trend before the policy implementation is parallel to the treated cities. I manually calculate city and year weights in the same vein of what Arkhangelsky et al. (2021) did, following Chen et al. (2024).

To construct city and year weight for Equation (1), I estimate the following SDID model:

$$(\hat{\beta}^{\text{sdid}}, \hat{\mu}, \hat{\sigma}, \hat{\gamma}, \hat{\tau}) = \arg\min_{\tau,\mu,\sigma,\gamma,\beta} \left\{ \sum_{c=1}^{N} \sum_{t=1}^{T} (Y_{ct} - \mu - \sigma_c - \tau_t - X_{ct}\gamma - W_{ct}\beta)^2 \, \hat{\omega}_c^{\text{sdid}} \hat{\lambda}_t^{\text{sdid}} \right\} \quad (7)$$

Where $W_{ct} = \mathbb{1}\{T_c\} \times Post_t$, which is the treatment indicator. To account for the heterogeneous growth rate of different cities, I control for total city population and firm average wage (both in log form) in X_{ct}. Additionally, to account for different trade shocks, I also control for the log of total export value.

As for Equation (2), a straightforward way to deal with this is to apply weight from Equation (1) directly into (2). However, the parallel trend assumption is violated using this approach. An explanation for this is that the calculated weight only matches parallel pre-trend at the whole city level, whereas those cities might have a heterogeneous pattern for industrial structure, which results in the parallel trend assumption being violated in the triple-difference setting.

As noted in Olden and Møen (2022), the triple-difference estimator can be computed as the difference between two difference-in-differences estimators, but it requires only one parallel trends assumption for a causal interpretation. This is because any common bias in the two DID estimators cancels out. In my setting, where I estimate heterogeneous trends between polluting and less polluting sectors, this implies that the counterfactual control group must be constructed such that the relative shares of polluting and less polluting sectors are similar to those in the treated cities, ensuring any bias affects both groups equally.

Given the above considerations, I calculate the weight from another SDID specification to address this issue. Particularly, I estimate the following SDID model:

$$(\hat{\beta}^{\text{sdid}}, \hat{\mu}, \hat{\sigma}, \hat{\gamma}, \hat{\tau}) = \arg\min_{\tau,\mu,\sigma,\gamma,\beta} \left\{ \sum_{c=1}^{N} \sum_{t=1}^{T} \left(ln(\frac{Y1_{ct}}{Y0_{ct}}) - \mu - \sigma_c - \tau_t - X_{ct}\gamma - W_{ct}\beta \right)^2 \hat{\omega}_c^{\text{sdid}} \hat{\lambda}_t^{\text{sdid}} \right\} \tag{8}$$

The only difference between this model and Equation (7) lies in the outcome variable. $Y1_{ct}$ and $Y0_{ct}$ refer to the outcomes from the top quintile polluting sectors and the remaining aggregate sectors, respectively. The calculated weight ensures that, prior to policy implementation, the control group has a parallel trend in terms of industrial structure (ratio) in polluting and less polluting sectors with the treated cities.

The weights used in the formal analysis have the following form:

$$Weight_{ct} = CityWeight_c \times YearWeight_t \tag{9}$$

A different weight is calculated for each outcome variable of interest. At last, the same procedure is applied when analyzing the neighboring cities.

B Additional Tables

Table B1: Match Rate by Treatment Group

	(1) Match Rate
$\mathbb{1}\{T\}$	-0.019
	(0.247)
$\mathbb{1}\{N\}$	0.005
	(0.739)
Sector FE	Y
Year FE	Y
Observations	5,752
R-squared	0.321

Table B2: Effect on COD Intensity

	(1) Treated	(2) Neighbor
$\mathbb{1}\{T\}$ × Post	0.029	0.090
	(0.878)	(0.545)
Pol × Post	-0.061	-0.060
	(0.683)	(0.682)
$\mathbb{1}\{T\}$ × Post × Pol	-0.102	-0.172
	(0.626)	(0.343)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.073	-0.082
Observations	2,257	3,323
R-squared	0.722	0.671
City-Sector FE	Yes	Yes
Year FE	Yes	Yes

Notes: P-values in parentheses. Standard errors clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table B3: Effects on Neighboring Cities: Controlling for City-Sector and Sector-Year FEs

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(SO2e_{tot})$	ln(SO2e/Out)	ln(SO2g/Out)	ln(Nfirms)	ln(Output)	ln(Emp)	ln(Cap)
$\mathbb{1}\{N\}$ × Post	0.158	0.013	0.003	0.065	0.066	-0.035	-0.018
	(0.278)	(0.907)	(0.978)	(0.303)	(0.381)	(0.542)	(0.783)
$\mathbb{1}\{N\}$ × Post × Pol	-0.006	-0.051	-0.055	0.038	0.138*	0.079	0.240***
	(0.967)	(0.684)	(0.667)	(0.335)	(0.093)	(0.113)	(0.001)
$\hat{\beta}_1 + \hat{\beta}_3$	0.152	-0.038	-0.052	0.103	0.204	0.044	0.222
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	3,778	3,090	3,091	3,900	3,510	3,900	3,510
R-squared	0.799	0.798	0.807	0.949	0.952	0.960	0.940

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table B4: Effects on Treated Cities: Controlling for City-Sector and Sector-Year FEs

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(SO2e_{tot})$	ln(SO2e/Out)	ln(SO2g/Out)	ln(Nfirms)	ln(Output)	ln(Emp)	ln(Cap)
$\mathbb{1}\{T\}$ × Post	0.442**	0.086	0.108	0.181***	0.142*	0.002	0.125
	(0.017)	(0.502)	(0.398)	(0.006)	(0.074)	(0.974)	(0.136)
$\mathbb{1}\{T\}$ × Post × Pol	-0.556**	-0.297**	-0.288*	-0.024	-0.067	-0.071	-0.089
	(0.014)	(0.046)	(0.053)	(0.563)	(0.559)	(0.357)	(0.506)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.114	-0.210	-0.180	0.157	0.075	-0.069	0.036
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Sector-Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	2,563	2,089	2,089	2,640	2,376	2,640	2,376
R-squared	0.795	0.798	0.806	0.967	0.962	0.972	0.950

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table B5: Effects on Neighboring Cities: Without SDID Weight

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln($SO2e_{tot}$)	ln(SO2e/Out)	ln(SO2g/Out)	ln(Nfirms)	ln(Output)	ln(Emp)	ln(Cap)
$\mathbb{1}\{N\} \times$ Post	0.037	0.003	0.018	0.042	0.036	-0.072	-0.024
	(0.800)	(0.984)	(0.888)	(0.532)	(0.672)	(0.304)	(0.757)
Pol $\times$ Post	-0.042	0.332***	0.347***	-0.019	-0.324***	-0.302***	-0.324***
	(0.747)	(0.007)	(0.005)	(0.564)	(0.000)	(0.000)	(0.000)
$\mathbb{1}\{N\} \times$ Post $\times$ Pol	0.100	-0.101	-0.125	0.064	0.201**	0.149**	0.298***
	(0.521)	(0.474)	(0.370)	(0.132)	(0.032)	(0.024)	(0.001)
$\hat{\beta}_1 + \hat{\beta}_3$	0.137	-0.098	-0.107	0.106	0.237	0.077	0.274
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	3,778	3,778	3,778	3,900	3,900	3,900	3,900
R-squared	0.790	0.776	0.787	0.939	0.944	0.945	0.918

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table B6: Effects on Treated Cities: Without SDID Weight

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln($SO2e_{tot}$)	ln(SO2e/Out)	ln(SO2g/Out)	ln(Nfirms)	ln(Output)	ln(Emp)	ln(Cap)
$\mathbb{1}\{T\} \times$ Post	0.313	0.032	0.083	0.167**	0.124	-0.027	0.131
	(0.103)	(0.803)	(0.520)	(0.015)	(0.137)	(0.675)	(0.133)
Pol $\times$ Post	-0.195	0.305**	0.317**	-0.020	-0.352***	-0.308***	-0.346***
	(0.222)	(0.015)	(0.012)	(0.536)	(0.000)	(0.000)	(0.000)
$\mathbb{1}\{T\} \times$ Post $\times$ Pol	-0.360	-0.262*	-0.275*	-0.005	-0.013	-0.006	-0.045
	(0.127)	(0.081)	(0.065)	(0.916)	(0.909)	(0.945)	(0.740)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.047	-0.230	-0.192	0.162	0.111	-0.033	0.086
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	2,563	2,563	2,563	2,640	2,640	2,640	2,640
R-squared	0.772	0.778	0.790	0.964	0.955	0.963	0.936

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

Table B7: Annual Percentage of SOEs by Region

	Firms (%)			Output (%)			SO_2 Emission (%)		
	Treated	Neighbor	Control	Treated	Neighbor	Control	Treated	Neighbor	Control
1998	32.3	43.9	37.9	51.9	50.8	39.0	76.98	78.68	73.03
1999	31.2	42.3	35.9	51.2	49.8	36.9	76.34	77.97	73.42
2000	27.8	37.8	30.0	50.6	49.6	34.5	74.96	77.42	68.33
2001	23.6	31.2	24.1	47.7	45.8	31.2	70.55	68.33	58.21
2002	20.1	25.4	20.1	44.0	41.4	27.9	65.84	62.62	65.08
2003	16.0	19.8	15.8	41.5	38.6	25.0	63.60	60.49	60.17
2004	10.5	12.8	10.4	36.5	34.5	23.4	50.58	51.79	54.38
2005	9.7	10.5	8.6	34.8	32.3	21.2	57.33	49.51	39.05
2006	8.2	8.4	7.1	31.9	29.4	19.6	54.84	48.92	41.66
2007	6.7	6.5	5.5	30.4	26.7	18.2	55.62	44.37	42.79

Table B8: Annual Percentage of SOEs by Region (Polluting Sectors Only)

	Firms (%)			Output (%)			SO_2 Emission (%)		
	Treated	Neighbor	Control	Treated	Neighbor	Control	Treated	Neighbor	Control
1998	34.4	47.1	47.0	62.5	66.4	63.2	78.4	80.5	73.9
1999	33.2	45.9	45.9	61.4	65.0	60.3	76.2	79.9	71.9
2000	30.3	42.2	41.2	59.8	63.8	59.1	73.8	78.3	66.5
2001	26.6	36.8	34.7	56.2	61.4	53.7	69.5	68.3	58.5
2002	23.1	31.7	31.4	52.7	54.7	50.1	68.2	62.4	64.9
2003	19.6	25.6	25.9	49.3	50.8	44.4	60.6	58.3	57.2
2004	12.6	17.0	19.3	38.5	42.9	38.2	41.6	51.4	54.1
2005	12.2	14.7	16.5	36.7	40.6	37.4	43.2	49.8	35.8
2006	10.4	12.1	14.0	33.4	39.1	35.4	43.2	48.5	38.1
2007	9.0	10.3	11.7	32.5	36.1	32.3	40.6	43.4	42.5

Notes: Each cell reports the percentage of state-owned enterprises (SOEs) in terms of number of firms, total output, or SO_2 emissions for polluting sectors only. Values are percentages rounded to one decimal place.

Table B9: Effect on Capital Stock by State-Ownership and Region

	Treated Cities		Neighbor Cities	
	(1)	(2)	(3)	(4)
	SOEs	Non-Soes	SOEs	Non-Soes
$\mathbb{1}\{T\} \times$ Post	0.406***	0.054	-0.041	0.183**
	(0.000)	(0.485)	(0.648)	(0.032)
Pol $\times$ Post	-0.193*	0.062	-0.149*	0.085
	(0.066)	(0.463)	(0.090)	(0.319)
$\mathbb{1}\{T\} \times$ Post $\times$ Pol	-0.187	-0.077	0.289***	-0.017
	(0.315)	(0.530)	(0.007)	(0.872)
$\hat{\beta}_1 + \hat{\beta}_3$	0.219	-0.023	0.248	0.166
Observations	2,322	2,268	3,420	3,384
R-squared	0.900	0.940	0.883	0.921
City-Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: P-values in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

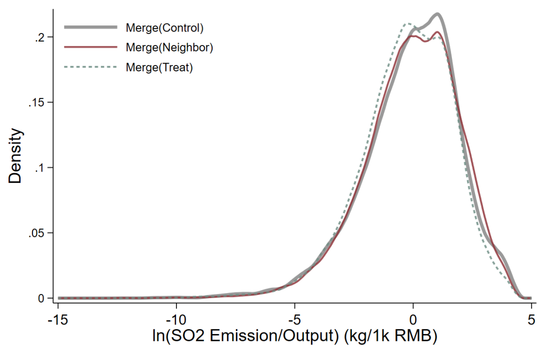
Table B10: Effects on Cross-Province Neighbor Cities

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\ln(\text{SO2e}_{\text{tot}})$	ln(SO2e/Out)	ln(SO2g/Out)	ln(Nfirms)	ln(Output)	ln(Emp)	ln(Cap)
$\mathbb{1}\{N\}$ × Post	-0.177	-0.346	-0.358	-0.110	0.088	-0.111	-0.121
	(0.579)	(0.290)	(0.274)	(0.358)	(0.588)	(0.329)	(0.372)
Pol × Post	0.090	0.293	0.303	-0.006	-0.247***	-0.219***	-0.266***
	(0.624)	(0.210)	(0.200)	(0.864)	(0.001)	(0.000)	(0.000)
$\mathbb{1}\{N\}$ × Post × Pol	0.065	0.227	0.197	0.055	0.003	0.104	0.300*
	(0.874)	(0.524)	(0.575)	(0.518)	(0.980)	(0.198)	(0.063)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.112	-0.119	-0.161	-0.055	0.092	-0.007	0.179
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	1,690	1,383	1,383	1,720	1,584	1,760	1,584
R-squared	0.800	0.721	0.727	0.919	0.942	0.948	0.932

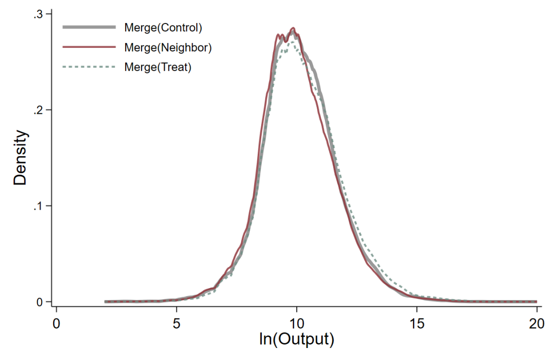
Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

C Additional Figures

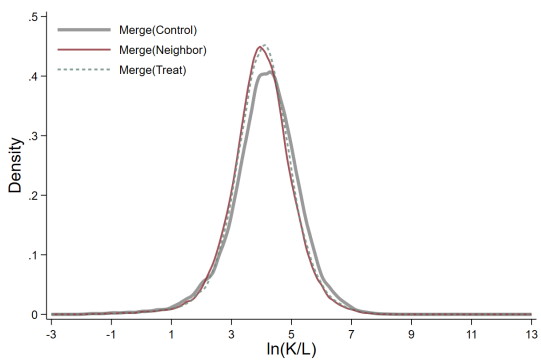
Figure C1: Distribution of Key Stats by Treatment Groups



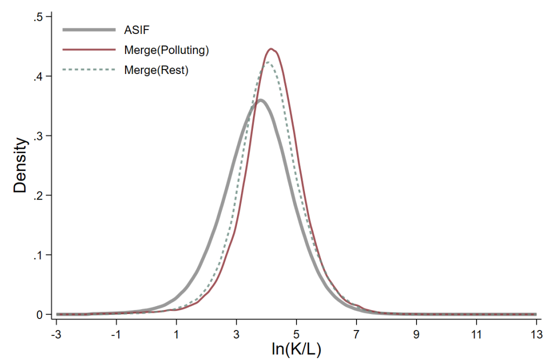
(a) Emission Intensity (by Region)



(b) Output (by Region)



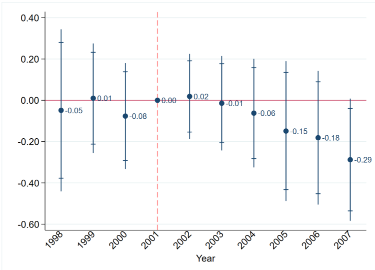
(c) K/L (by Region)



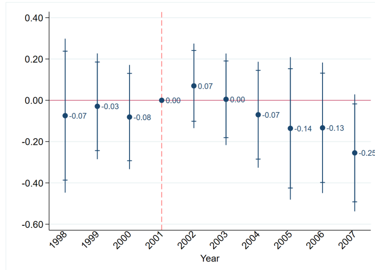
(d) K/L (by Sector)

Note: This panel compares key stats by treatment group. The results show that different groups have a similar distribution. Additionally, panel (d) shows that polluting and less polluting sectors have a similar pattern as well.

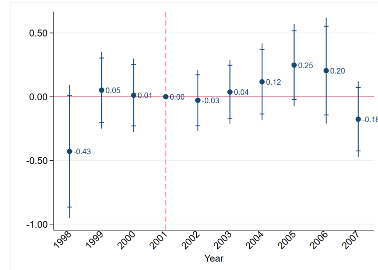
Figure C2: Pre-trend for Aggregate Effects in Treated Cities (Raw DID)



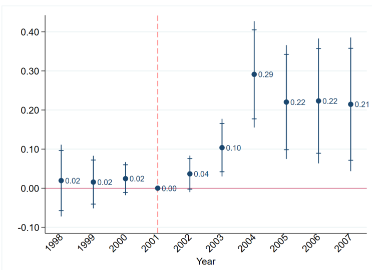
(a) SO_2 Emission Intensity



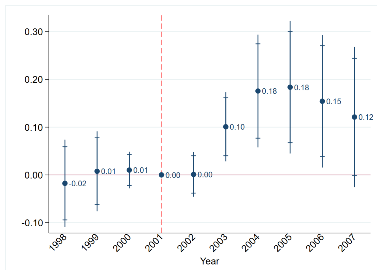
(b) SO_2 Generation Intensity



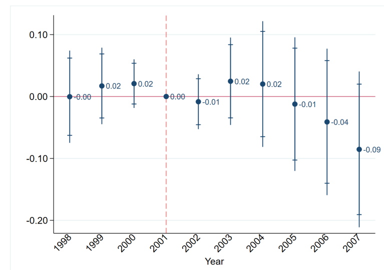
(c) Total SO_2 Emission



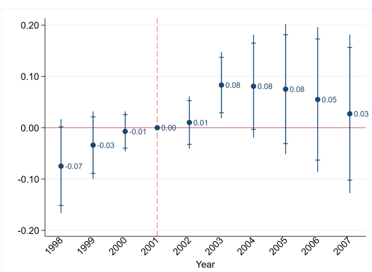
(d) Nfirms



(e) Output



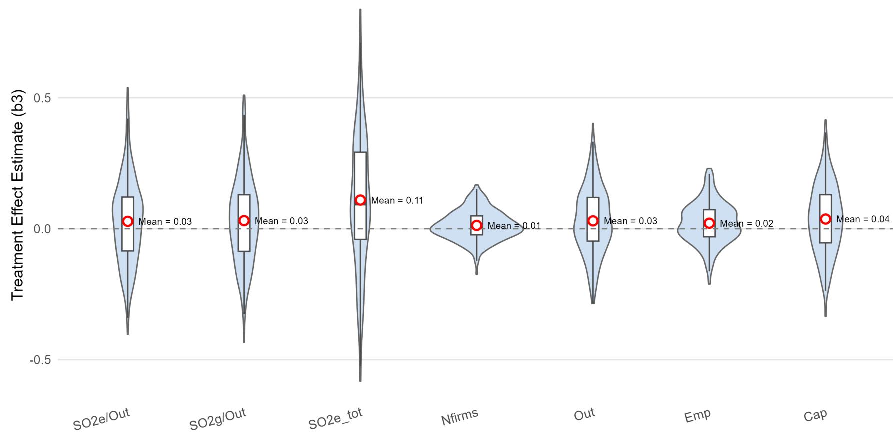
(f) Employment



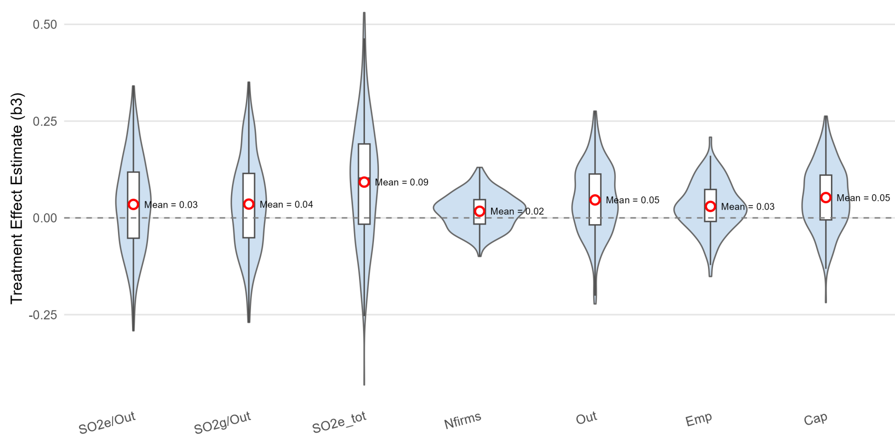
(g) Capital Stock

Note: This is the event study plot for equation (1) without adding SDID weights.

Figure C3: Distribution of $\hat{\beta}_3$ for Randomly Treated Cities



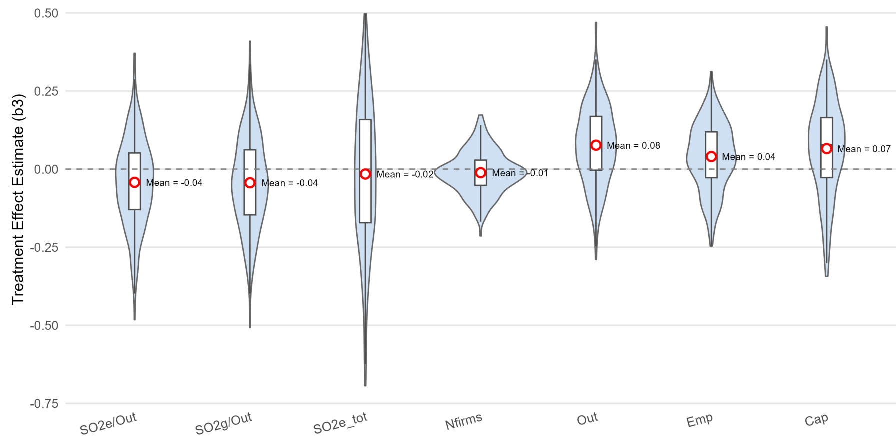
(a) Treated Cities



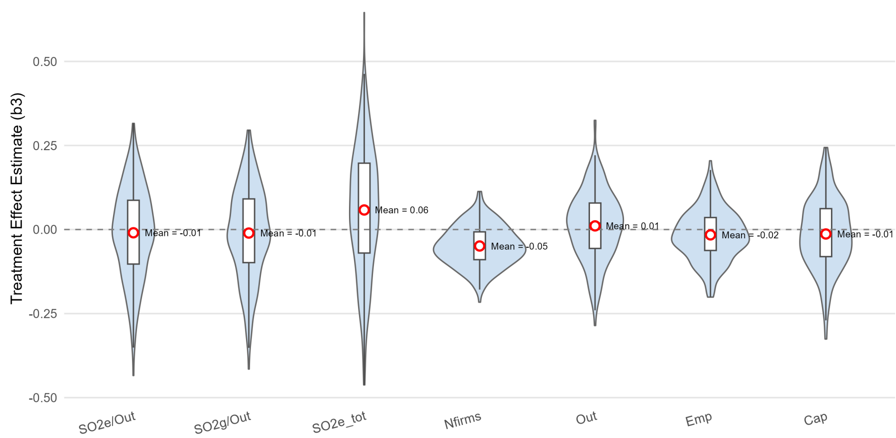
(b) Neighboring Cities

Note: Blue area represents density of distribution for the $\hat{\beta}_3$, red circle represents the mean across all 250 replications, and white box represents range within one standard-deviation of the distribution. Figure a is for the distributions of $\hat{\beta}_3$ for treated cities, while Figure b is for neighboring cities.

Figure C4: Distribution of $\hat{\beta}_3$ for Random Polluting Sectors



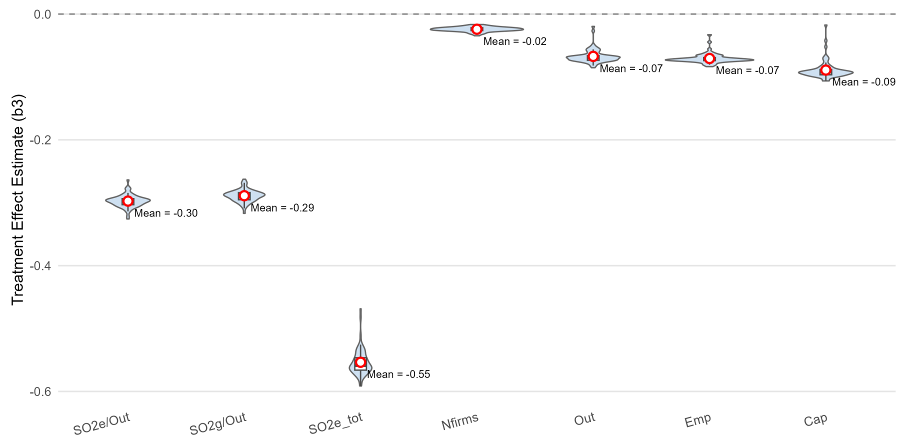
(a) Treated Cities



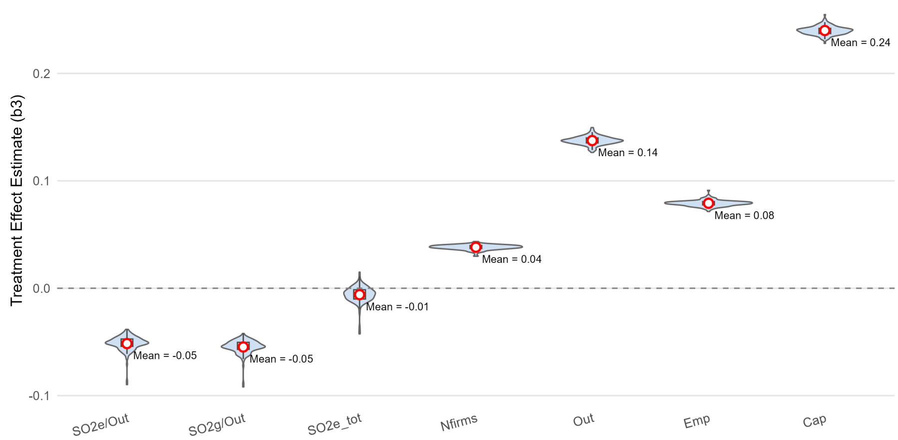
(b) Neighboring Cities

Note: Blue area represents density of distribution for the $\hat{\beta}_3$, red circle represents the mean across all 250 replications, and white box represents range within one standard-deviation of the distribution. Figure a is for the distributions of $\hat{\beta}_3$ for treated cities, while Figure b is for neighboring cities.

Figure C5: Distribution of $\hat{\beta}_3$ for Leave-One-Out Cities



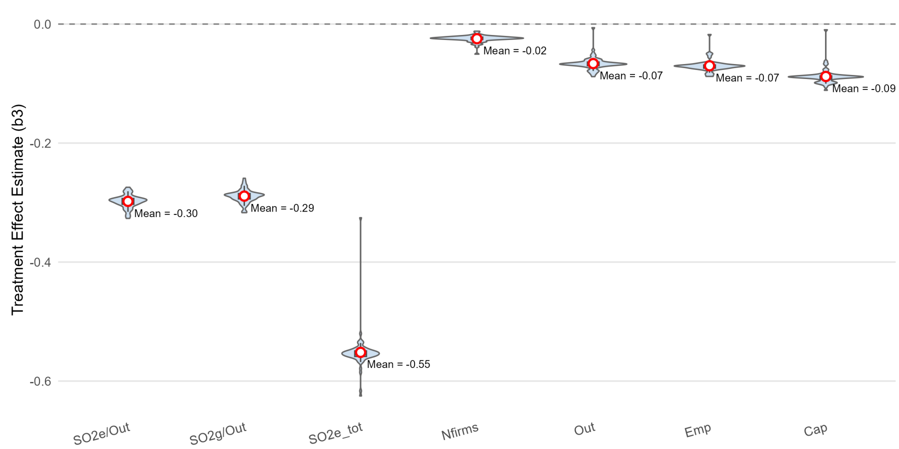
(a) Treated Cities



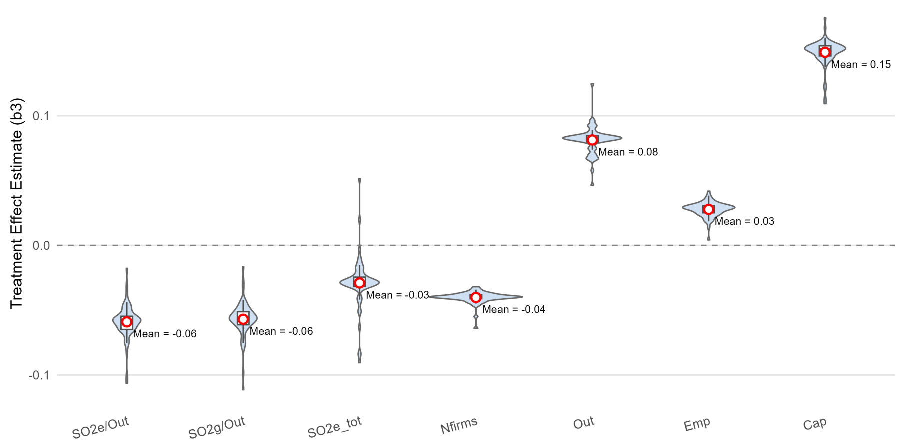
(b) Neighboring Cities

Note: Blue area represents density of distribution for the $\hat{\beta}_3$, red circle represents the mean across all leave-one-out replications, and white box represents range within one standard-deviation of the distribution. Figure a is for the distributions of $\hat{\beta}_3$ for treated cities, while Figure b is for neighboring cities.

Figure C6: Distribution of $\hat{\beta}_3$ for Leave-One-Out Sectors



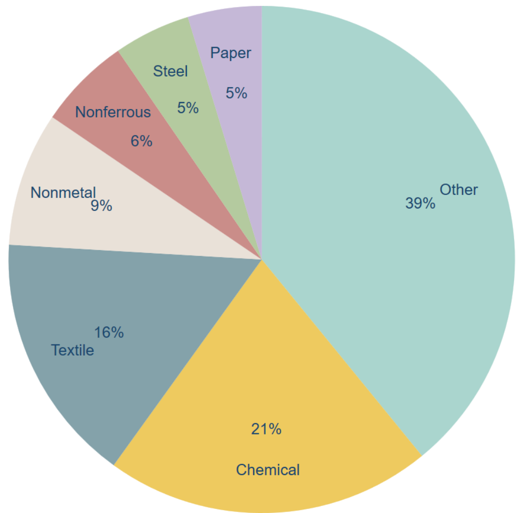
(a) Treated Cities



(b) Neighboring Cities

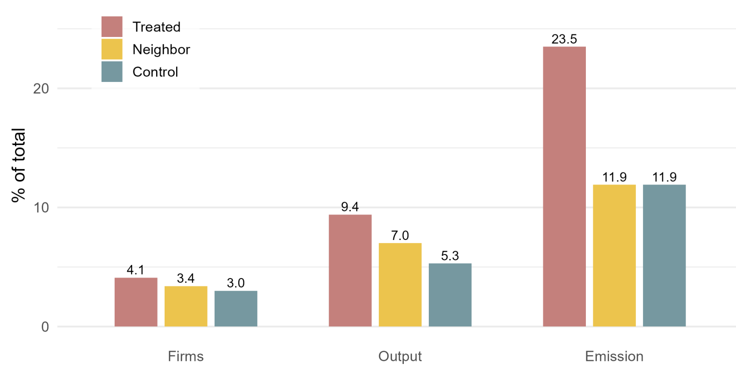
Note: Blue area represents density of distribution for the $\hat{\beta}_3$, red circle represents the mean across all leave-one-out replications, and white box represents range within one standard-deviation of the distribution. Figure a is for the distributions of $\hat{\beta}_3$ for treated cities, while Figure b is for neighboring cities. Notably, the one replication for the total SO_2 emission in the treated city (with $\hat{\beta}_3$ around -0.3) is due to the drop of the steelmaking sector.

Figure C7: Sectoral Distribution of Switching Firms



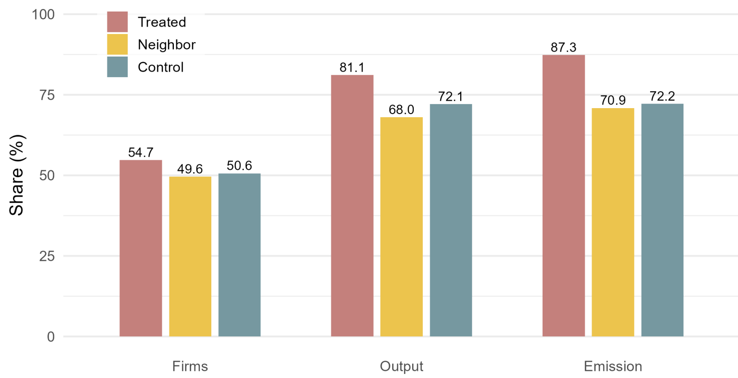
Notes: The pie chart shows the share of two-digit sectors among all switching firms; for example, about 21 % of switching firms are in chemical sectors.

Figure C8: Share of Switching Firms by Region



Notes: This figure plots the share of key outcomes (number of firms, gross value output, as well as SO_2 emission) by treatment status.

Figure C9: Share of Non-Privatized SOEs in 2007 by Region



Notes: This figure plots the share of key outcomes (number of firms, gross value output, as well as SO_2 emission) by treatment status.