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 studying China's Key Cities Air Pollution Control (KCAPC) program, a city-specific air-quality policy. Using a synthetic difference-in-differences design to address targeted policy placement, I estimate the policy's effects on sulfur dioxide (SO_2) emissions and industrial composition in treated cities and their non-treated neighbors. I find limited net reductions in SO_2 emissions but strong evidence of spatial reallocation: within five years, treated cities reallocate production toward cleaner sectors, while neighboring cities expand output and capital in pollution-intensive industries, consistent with leakage. Mechanism evidence suggests that this reallocation was driven primarily by province-level coordination through state-owned enterprises, with a secondary role for firm-level product switching. These findings show that within-country environmental regulation can generate PHE-type outcomes in the short run, and that policies designed at one administrative level may induce unintended reallocation when coordination occurs at a higher level.

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1 Motivation and Introduction

Environmental regulations are typically set and enforced within political boundaries, but their economic and environmental consequences often extend beyond those borders. This spatial dimension of regulation has become increasingly salient in both policy debates and academic research (Balboni and Shapiro, 2025). A central concern is the Pollution Haven Effect (PHE): when regulation raises compliance costs in pollution-intensive activities, affected production may contract locally and expand in less regulated places, either through changes in production across regions (Hanna, 2010; Copeland et al., 2022; Chen et al., 2025) or through firms' location choices (Henderson, 1995; Harrison et al., 2015). Accounting for these spatial interactions is essential for effective policy design, because improvements in one jurisdiction may be offset by deterioration elsewhere.

Despite extensive study of the PHE, empirical evidence of large, regulation-induced changes in industrial structure remains limited in the cross-country context. Most cross-country work finds modest structural shifts (Copeland et al., 2022; Levinson, 2023; Shapiro and Walker, 2018), with notable exceptions in specific industries (Tanaka et al., 2022). One explanation is that cross-country reallocation is constrained by trade costs, productivity differences, and other sources of comparative advantage that can dominate the effects of environmental regulation (Duan et al., 2021). This motivates studying the PHE within a single country, where internal trade frictions are smaller and institutional differences are less stark, yet policy stringency can still vary sharply across jurisdictions.

This paper revisits the PHE in a subnational setting by studying China's Key Cities for Air Pollution Control (KCAPC) program, a national air-quality initiative that imposed city-specific pollution control requirements. I examine how KCAPC reshaped both environmental performance and industrial composition in regulated cities and in adjacent, non-treated cities that plausibly served as destinations for displaced activity. The analysis addresses three questions: (i) What is the magnitude of regulation-induced reallocation across space and across sectors? (ii) Through which firm-level margins do cities adjust (e.g., within-firm product adjustment versus entry and exit)? (iii) To what extent is observed reallocation driven by market forces versus politically mediated 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 KCAPC, implemented in 2002 across 66 cities.[1] In the pre-policy period (2001), firms surveyed in these second-round cities accounted for about 21% of national manufacturing output and 30% of manufacturing-related sulfur dioxide (SO_2) emissions, the primary pollutant studied in this paper.[2]

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 roughly the top 85% of county-level emissions and reports pollutant outcomes, including SO_2. The ASIF covers all state-owned firms and non-state firms with annual revenues above 5 million RMB and provides detailed financial, operational, and locational information. Merging AESPF and ASIF yields a city–sector panel from 1998–2007 that I use to evaluate KCAPC's effects on emissions, emissions intensity, industrial composition, and economic outcomes.

To estimate causal effects, I use the synthetic difference-in-differences (SDID) method of Arkhangelsky et al. (2021), which combines synthetic control and difference-in-differences to

[1] An earlier round in 1998 targeted 47 additional cities, but data limitations prevent a comparable analysis for that cohort.

[2] Manufacturing SO_2 emissions largely arise from burning sulfur-containing fossil fuels (e.g., coal and oil) and from specific industrial processes (e.g., metal smelting and petrochemicals). Short-term exposure to SO_2 harms respiratory health and contributes to particulate matter formation. For background, see EPA Sulfur Dioxide Basics.

address targeted policy placement and heterogeneous pre-trends. I study both average effects and heterogeneous effects across sectors. In particular, I distinguish between the top-quintile most pollution-intensive industries (ranked by pre-policy SO_2 intensity; hereafter, "polluting sectors") and less pollution-intensive industries. To identify spatial reallocation directly, I separately estimate KCAPC's impacts on (i) treated cities and (ii) their adjacent, non-treated neighbors. In both cases, I construct control groups from distant, non-neighboring cities to avoid contamination from spillovers.

Separately estimating effects for treated cities and for neighboring cities matters for both identification and interpretation. Excluding potentially contaminated neighbors from the control group reduces bias in the estimated treatment effects for regulated cities. Moreover, estimating neighbor effects directly provides a test of whether spillovers operate through PHE-type relocation rather than through purely local abatement. This approach complements existing firm-level studies of KCAPC (Liu et al., 2021; Viard et al., 2022), which typically rely on geographically proximate controls and therefore may understate spillovers when neighbors are themselves affected.

Using this framework, I document that KCAPC disproportionately tightened environmental performance in pollution-intensive sectors and induced substantial spatial reallocation. In treated cities, the policy reduces emissions intensity in polluting sectors and shifts the composition of SO_2 emissions toward less pollution-intensive sectors. On the economic side, I find increases in output and capital in less polluting sectors and smaller (or more muted) changes in polluting sectors; however, I do not find robust evidence of large, differential specialization changes within treated cities over the short horizon, consistent with a composition shift in pollution rather than a wholesale reallocation of economic activity across sectors. In contrast, effects in neighboring cities are larger: relative to distant controls, neighboring cities experience significant increases in total emissions and output, with output growth concentrated in polluting sectors. These patterns are robust to placebo tests with randomized treatment assignment, alternative samples (e.g., excluding outliers), and a range of specification checks.

To clarify mechanisms, I examine three channels: within-firm product adjustment, extensive-margin dynamics (entry and exit), and non-market reallocation. The evidence points primarily to the third. First, I document product "switching" among treated-city firms toward less pollution-intensive products; however, excluding switchers leaves the main patterns largely unchanged. Second, while polluting sectors in treated cities exhibit somewhat higher exit and lower net entry, these extensive-margin responses are quantitatively small. Third, ownership-based heterogeneity indicates that reallocation is largely driven by state-owned enterprises (SOEs): SOEs expand in less polluting sectors within treated cities and expand in more pollution-intensive sectors in neighboring cities, whereas effects for non-SOEs are smaller and often statistically insignificant. Consistent with a province-level coordination mechanism, spillover effects are negligible for cross-province neighbors. Taken together, these results suggest that KCAPC-induced reallocation operates primarily through politically mediated channels via SOEs, rather than through within-firm product switching or entry–exit dynamics.

Although China's institutional setting is distinctive, the mechanisms highlighted here are not unique. Evidence from the United States shows that plants regulated under the Clean Air Act (CAA) attainment designations can offset regulated releases by increasing emissions at other plants within the same firm (Gibson, 2019). More recently, the Good Neighbor Plan (GNP) issued in 2023 targeted selected upwind states and industries for NO_X emissions.[3] While the pollutants and institutional details differ, these examples underscore a general point: when regulation is uneven across space, compliance can induce reallocation rather than net reduction, potentially creating nearby "pollution havens."

This paper contributes to the literature on the Pollution Haven Effect and 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.,

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

2022); see Copeland et al. (2022) for a comprehensive review. Relative to cross-country evidence that finds output and intensity channels rather than industrial-structure shifts play a major role (Cherniwchan, 2017; Holladay, 2016; Najjar and Cherniwchan, 2021; Shapiro and Walker, 2018), I provide within-country evidence that composition changes and spatial reallocation can occur over a short horizon. Relative to within-country location-choice studies that often rely on conditional logit designs (Wu et al., 2017; Wang et al., 2019; Yang et al., 2018), which present challenges for causal identification and policy counterfactuals, I use SDID to address targeted policy placement and to estimate both treated-city and neighbor effects. Finally, by documenting ownership-based heterogeneity consistent with province-level coordination through SOEs, I highlight a political-economy mechanism that can generate rapid PHE-type outcomes, complementing work that emphasizes slower market-driven adjustment (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, the paper speaks to heterogeneous enforcement and the principal-agent problem in environmental governance. Prior work documents uneven enforcement across regions (Duflo et al., 2013; Du and Li, 2023) and more lenient regulation in border areas (Cai et al., 2016; Lipscomb and Mobarak, 2016; Monogan III et al., 2017). I show that, in addition to within-city enforcement differences, province-level coordination through SOEs can reallocate production across city borders, implying that policy effectiveness depends on whether the unit of regulation aligns with the unit of coordination. This mechanism differs from accounts that emphasize city-level career incentives and local tradeoffs (Chen et al., 2018) and highlights an additional layer through which decentralization can shape environmental outcomes.

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 rising concerns about air pollution, China elevated environmental protection in the Tenth Five-Year Plan (2001–2005).[4] One major initiative under this framework was the Key Cities for Air Pollution Control (KCAPC) program, a city-targeted regulation administered by the Ministry of Environmental Protection (MEP) that aimed to improve urban air quality.

KCAPC was introduced in 1998 and later expanded. In the first round, the central government designated 47 prefecture-level cities, which are primarily provincial capitals, special economic zones, and major tourist destinations, as key targets. The second round

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

added 66 cities, designated in December 2002.[5] These cities were required to meet air-quality targets by 2005 based on China's Class II Ambient Air Quality Standard (GB3095-2000) for SO_2 and five other pollutants.

Selection into the second round was primarily based on failure to meet the GB3095-2000 standards in 2000, together with additional criteria. After assessing contemporaneous pollution conditions and city-level economic characteristics, the central government selected 66 cities guided by three considerations: (i) overall economic development and environmental pollution levels; (ii) inclusion in the Two Control Zones (TCZ), a major national policy targeting SO_2 and acid rain control at the city level;[6] and (iii) cultural-heritage cities deemed in urgent need of environmental protection. Figure 1 maps the spatial distribution of both KCAPC rounds. Designated cities are concentrated in more industrialized eastern and central provinces, with relatively sparse coverage in the west, consistent with the policy's emphasis on major urban industrial emitters and areas with higher administrative capacity.

To comply with the standards, treated cities were subject to a package of regulatory instruments described in a follow-up directive.[7] Provincial leaders and city governments were instructed to restructure local industrial activity by shutting down, suspending, or relocating highly polluting firms, particularly those using outdated technology and exhibiting high energy consumption and excessive emissions. The directive also required the installation of monitoring equipment and encouraged fuel switching toward cleaner energy sources (e.g., electricity and natural gas). Complementary measures included reducing raw coal consumption, promoting clean-coal technologies, establishing high-pollution fuel ban zones, and providing financial support for upgrades.

A key feature of KCAPC was its enforcement and accountability structure. Prior research finds that KCAPC reduced air pollution in targeted cities (Liu et al., 2021; Viard et al., 2022),

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

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

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

consistent with strong incentives for local enforcement. Cities in the first round were assessed directly by the MEP, whereas second-round cities were evaluated by provincial environmental protection bureaus, which then reported assessments to the MEP.

As emphasized in the Tenth Five-Year Plan, environmental protection responsibilities were delegated to local governments and formalized through "letters of responsibility" signed by mayors specifying environmental targets for their term.[8] Performance was reported upward, and state media disseminated daily air-quality readings for covered cities. Because environmental outcomes could influence cadre evaluations and promotion prospects, these arrangements plausibly strengthened enforcement incentives. At the same time, they may have increased incentives to displace pollution-intensive activity to nearby jurisdictions that were not directly regulated, creating scope for cross-border leakage.

Finally, KCAPC enforcement was not uniform across industries. The Tenth Five-Year Plan emphasized controlling emissions from sectors such as metallurgy, petrochemicals, cement, paper, and textiles. In a subsequent government review,[9] authorities highlighted technological upgrading in these industries and reported continued output growth alongside declining pollution intensity.

Due to data availability constraints, I focus on the second round of KCAPC implemented in 2002.

3 Data

3.1 Annual Survey of Industrial Firms

I use the Annual Survey of Industrial Firms (ASIF) to construct city–sector economic outcomes over 1998–2007. ASIF covers all state-owned enterprises (SOEs) and non-state firms with annual sales above 5 million RMB (approximately $696,000). Firms are classified un-

[8]For an official description, see Urban Environmental Protection in China (in Chinese).

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

der China's National Industrial Classification, which includes mining, manufacturing, and utilities (production and supply of electricity, gas, and water). Collected by the National Bureau of Statistics (NBS), ASIF contains detailed firm-level accounting information and provides the micro-level foundation for industrial aggregates reported in the China Statistical Yearbook.

ASIF is widely used in empirical research on China. I follow standard cleaning procedures. Specifically, I drop observations with missing or non-positive values for key variables such as gross output, employment, and capital stock. I also drop observations that violate basic accounting identities or plausibility restrictions, including cases where liquid assets, fixed assets, or net fixed assets exceed total assets, or where current depreciation exceeds cumulative depreciation. These procedures follow Yu (2015) and Brandt et al. (2012).

Using the cleaned data, I aggregate firm-level measures to the city–sector–year level, including total gross sales revenue, total real capital stock, total employment, and the number of firms. I also construct the average wage as a proxy for local labor costs.

3.2 Annual Environmental Survey of Polluting Firms

The Annual Environmental Survey of Polluting Firms (AESPF)[10] is the most comprehensive firm-level environmental dataset available for China. Conducted by the Ministry of Environment, the survey reports firms' environmental performance, including emissions of major pollutants, pollution-abatement equipment, and energy use. 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% 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 En-

[10]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).

vironmental 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[11] to construct environmental outcome measures.

3.3 Other Data Sources

I supplement the firm microdata with city-level information from the China City Statistical Yearbook (CCSY), produced annually by the NBS. The CCSY provides socioeconomic statistics for municipal-level cities; I use population and GDP per capita. When these variables are missing (occasionally for smaller cities prior to 2000), I supplement them using city government annual reports. Information on KCAPC status and cohort assignment is obtained from official policy documents and government 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.

[11] 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.

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 provides additional evidence on representativeness. It reports sectoral SO_2 generation intensity and the sector shares in ASIF and in the merged sample. More pollution-intensive sectors are disproportionately represented among matched firms. To further characterize this selection, Figure 3 compares the distributions of firm-level emission intensity, output, and the capital–labor ratio across ASIF, AESPF, and the merged sample. The merged sample skews toward larger and more capital-intensive firms, which may also differ in pollution intensity.

This selection has implications for measuring sectoral pollution intensity. Because I use the merged sample to calculate SO_2 intensity and to classify sectors as polluting versus less polluting, the resulting measures primarily reflect the pollution profiles of larger firms. The key object for my analysis, however, is the *relative ranking* of sectoral pollution intensity rather than its level. I return to this issue in Section 4.2, where I describe the classification procedure and assess 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:

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

where Y_{sct} is the outcome for sector s in city c and year t. Pol_s is an indicator for highly pollution-intensive sectors (top quintile by pre-policy SO_2 intensity; see Section 4.2). σ_{sc} are city–sector fixed effects, which absorb time-invariant differences in baseline industrial composition across cities, and τ_t are year fixed effects. The coefficient β_3 captures whether KCAPC changes outcomes differentially in pollution-intensive sectors within treated cities.

Neighbors and spillovers. 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 adjacent non-treated cities as a separate "neighbor" group to estimate spillover effects. Specifically, I re-estimate (1) and (2), replacing

$\mathbb{1}\{T_c\}$ with $\mathbb{1}\{N_c\}$, an indicator for non-treated cities that share a border with a treated city. Both the treated-city analysis and the neighbor analysis rely on the assumption that sufficiently distant, non-neighboring cities are not materially affected by KCAPC.

4.2 Sector Classification and Data Validity Checks

Classifying pollution-intensive sectors. To study heterogeneity, I operationalize which industries are "polluting." As noted in Section 3.4, the merged ASIF–AESPF sample is skewed toward larger firms and more pollution-intensive sectors. The key object for my heterogeneity analysis is the *relative ranking* of sectoral pollution intensity rather than its level. This subsection describes the construction of this ranking and presents evidence supporting the stability of the 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 sensitivity to sparse sectors and extreme values, 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. Motivated by this pattern, I define $Pol_s = 1$ for top-quintile sectors (61 out of 308) and $Pol_s = 0$ otherwise in the heterogeneity analysis below.

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. These industries are concentrated among the top-quintile sectors in the data, suggesting that the intensity-based classification captures the policy's intended regulatory focus.

Sample construction and 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, which have distinct institutional and economic environments and limited data coverage.

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 concerns. 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. I address this concern in two ways.

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 ASIF–AESPF match rate for sector s in city c and year t. Table B1 shows no statistically significant differences in match rates across groups.

Second, I compare the distributions of firm-level emission intensity, output, and the capital–labor ratio across city groups (Figure C1). The distributions are similar between treated, neighbor, and control cities, suggesting that the merged sample does not differentially represent particular types of firms across groups.

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. Before presenting SDID estimates, I assess pre-treatment trends using a conventional event-study DID specification for treated cities without SDID weights. Figure C2 shows no statistically meaningful differential pre-trends for key outcomes prior to policy onset, supporting the use of a DID-type design. Nevertheless, because treatment selection is targeted and pre-trend fit can differ across outcomes and sectors, I use SDID as the main specification and report raw DID estimates as robustness checks in Section 5.5.

5 Results on Treated and Neighboring Cities

5.1 Effect of Reallocation on Neighboring Cities

I begin by examining whether KCAPC induced spatial reallocation of pollution-intensive activity across city borders. In this setting, the central empirical implication of the Pollution Haven Effect (PHE) is that tighter regulation in treated cities leads pollution-intensive production to expand in nearby, less regulated jurisdictions. Establishing such spillovers is central for distinguishing reallocation from purely local abatement.

I focus on non-treated cities that share a border with treated cities. Panel A of Table 6 reports SDID estimates, and Figure 6 shows no statistically meaningful differential pre-trends. Relative to distant control cities, neighboring cities experience a statistically significant 20.7%[12] increase in total SO_2 emissions, a 16.2% increase in output, and a 12.0% increase in capital stock. Columns 1, 2, and 5 indicate that the increase in emissions is driven primarily by higher output rather than rising emissions 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.

[12] For log-transformed outcomes, percent changes are computed as $100 \times (\exp(\hat{\beta}) - 1)$. Here, $\hat{\beta} = 0.188$, implying a 20.7% increase in SO_2 emissions. The same conversion is used throughout.

To make the heterogeneity more transparent, I report implied effects separately for less pollution-intensive sectors and for top-quintile pollution-intensive sectors. In less polluting sectors, the number of firms increases by 6.7%, output by 6.8%, and capital stock declines slightly (1.8%). In contrast, top-quintile polluting sectors exhibit a 10.9% increase in firm counts, a 22.7% rise in output, and a 24.9% increase in capital stock. While not all coefficients are individually statistically significant, the pattern of magnitudes is consistent with neighboring cities expanding pollution-intensive activity after KCAPC.

At the same time, Column 1 shows no statistically significant differential change in total SO_2 emissions between polluting and less-polluting sectors. This likely reflects offsetting forces: output expansion in less-polluting sectors and modest declines in emissions intensity within polluting sectors. Taken together, the results provide direct evidence of spillovers consistent with a within-country PHE operating across city borders.

Having established that pollution-intensive activity expands in neighboring cities, I next examine how KCAPC affected 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% increase in total output, driven mainly by a 19.5% 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%, 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%, implying that about 86.8% 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%, while those in less-polluting sectors increased by 55%. Given that top-quintile polluting sectors accounted for 73.3% of baseline emissions, the implied overall change corresponds to a 6.8% increase in aggregate emissions, which is slightly smaller than the direct city-level estimate.

The increase in emissions from less-polluting sectors appears to be driven by output expansion (Column 5), but the magnitudes imply that emissions rise disproportionately relative to output. One interpretation is compositional: firms initially operating in polluting sectors shift output toward less pollution-intensive product lines that are still nontrivial emitters. As shown in Section 6.1, this within-firm adjustment can rationalize rising emissions in the "less polluting" category even when regulation is tighter on the most pollution-intensive industries.

For economic outcomes in polluting sectors, Columns 4–7 show modest changes: output increases by 7.8% and the number of firms rises by 19.6%, again implying smaller average firm size. Importantly, the triple-difference coefficients for economic specialization are negative but statistically imprecise across outcomes, so the evidence does not support a large within-city reallocation of economic activity across sectors over the short horizon. Taken together, the treated-city results point to a shift in the composition of emissions across sectors and process-level improvements in pollution-intensive industries, rather than a strong reallocation of economic specialization within treated cities.

These findings differ from firm-level studies of KCAPC such as Liu et al. (2021) and Viard et al. (2022), which report significant reductions in firm-level emissions. Two differences can reconcile the results. First, my outcomes are sector-level aggregates that incorporate entry, exit, and reallocation across firms and sectors, whereas firm-level regressions isolate within-firm responses. Second, the control-group construction differs: both studies rely on geographically proximate controls (via propensity-score matching (Liu et al., 2021) or distance-based comparisons (Viard et al., 2022)), which may be contaminated if neighboring cities absorb displaced activity. If spillovers raise pollution and output in neighbors, then using those neighbors as controls would mechanically bias estimated treatment effects toward finding larger reductions in treated cities. The spillover estimates above provide direct evidence consistent with this concern.

5.3 Location Quotient Analysis

The treated and neighboring-city results suggest that KCAPC reshaped output and emissions in a manner consistent with PHE-type reallocation. As an additional validation, I examine changes in regional specialization using the Location Quotient (LQ), a standard measure in the agglomeration literature. LQ compares a sector's share of activity in a city to its share nationally:[13] values above one indicate relative specialization.

[13] $LQ_{rs} = \frac{N_{rs}/N_r}{N_s/N}$, where N_{rs} denotes activity in sector s and city r (measured by firms, output, employment, or capital), N_r is total activity in city r, N_s is total activity in sector s, and N is total activity across cities and sectors.

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).[14] 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.

5.4 Discussion

Overall, KCAPC disproportionately affects pollution-intensive sectors and generates meaningful spillovers to neighboring jurisdictions. In treated cities, emission intensity declines in pollution-intensive industries, but aggregate city-level emissions do not fall significantly because emissions shift toward less pollution-intensive sectors and economic activity expands. In neighboring cities, by contrast, both emissions and output increase significantly, with the

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

output expansion concentrated in pollution-intensive sectors.

Taken together, the results provide evidence consistent with a within-country Pollution Haven Effect. Regulation is associated with (i) a shift in the composition of pollution within treated cities away from the most pollution-intensive sectors and (ii) an expansion of pollution-intensive activity in neighboring cities. In the next section, I investigate the mechanisms underlying these adjustments.

5.5 Robustness Check

I conduct several robustness exercises to evaluate whether the results are sensitive to pollutant choice, treatment assignment, influential observations, and model specification.

5.5.1 Other Pollutant

To assess whether the results reflect SO_2-specific regulation rather than coincident environmental programs, I estimate KCAPC effects on chemical oxygen demand (COD), a common measure of water pollution.[15] Table B2 shows that estimated effects are small and statistically insignificant, supporting the interpretation that the baseline findings are 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[16] 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

[15] COD measures the oxygen required to chemically oxidize organic and inorganic compounds in water.
[16] Consistent with the actual number of treated cities after excluding three western provinces.

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[17] 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) 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.

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

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 estimate conventional DID models without synthetic weighting. Table B6 and Table B5 show estimates that are similar in sign and magnitude to the SDID results, indicating that the findings are not driven by 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.[18] 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 mis-

[18] 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).

classification 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% 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:

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

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

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.[19]

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 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)[20] 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

[19] 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.

[20] 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%.

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 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.[21] 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.[22]

[21] 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.

[22] SOEs are defined as all firms that were ever state-controlled during the sample period, given that former

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%[23] 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 asymmetry 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

SOEs may retain close ties with local governments.

[23]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%), 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.

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? This paper addresses these questions by studying China's Key Cities for Air Pollution Control (KCAPC) program, a national policy that imposed stricter emission controls on selected cities and disproportionately targeted pollution-intensive sectors. I evaluate both environmental outcomes (total emissions and pollution intensity) and economic outcomes (output, capital, and employment) at the city level and by sector.

Using a synthetic difference-in-differences design to construct counterfactuals under targeted policy placement, I document evidence consistent with a within-country Pollution Haven Effect. In treated cities, KCAPC reduces pollution intensity primarily in the most pollution-intensive (top-quintile) sectors, consistent with tighter regulation and cleaner production processes. At the same time, activity expands in neighboring non-treated cities, with output and capital growth concentrated in pollution-intensive sectors, consistent with spatial leakage of pollution-intensive production.

Mechanism evidence suggests that these patterns are not driven primarily by large-scale entry–exit responses or by within-firm switching of products alone. Instead, the adjustment appears to operate largely through non-market channels: state-owned enterprises expand in less polluting sectors within treated cities and expand in pollution-intensive sectors in neighboring cities, consistent with province-level coordination. Within-firm switching in principal activity is present and economically meaningful for switching firms, but excluding switchers leaves the main cross-city patterns essentially unchanged.

Overall, the findings highlight a general design problem for place-based environmental regulation: when regulation is implemented at a lower administrative level, emissions and production can be displaced to nearby jurisdictions. Policy effectiveness, therefore, depends on whether the *unit of regulation* aligns with the relevant *unit of coordination* for production decisions and enforcement. Designing environmental policy to anticipate inter-jurisdictional spillovers and to better align these units can improve both environmental effectiveness and the distribution of regulatory burdens.

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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)	(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							
$\mathbb{1}\{N\} \times$ 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							
$\mathbb{1}\{T\} \times$ 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							
$\mathbb{1}\{T\} \times$ 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 $\times$ 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)
$\mathbb{1}\{T\} \times$ Post $\times$ 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 $\mathbb{1}\{T\} \times$ Post and $\hat{\beta}_3$ represent $\mathbb{1}\{T\} \times$ Post $\times$ 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			
$\mathbb{1}\{T\} \times$ Post	-0.027**	-0.007	0.021
	(0.023)	(0.568)	(0.194)
Pol $\times$ Post	-0.013	-0.012	0.002
	(0.216)	(0.282)	(0.897)
$\mathbb{1}\{T\} \times$ Post $\times$ 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			
$\mathbb{1}\{N\} \times$ Post	-0.017	-0.013	0.004
	(0.186)	(0.285)	(0.804)
Pol $\times$ Post	-0.014	-0.014	0.001
	(0.180)	(0.203)	(0.949)
$\mathbb{1}\{N\} \times$ Post $\times$ 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

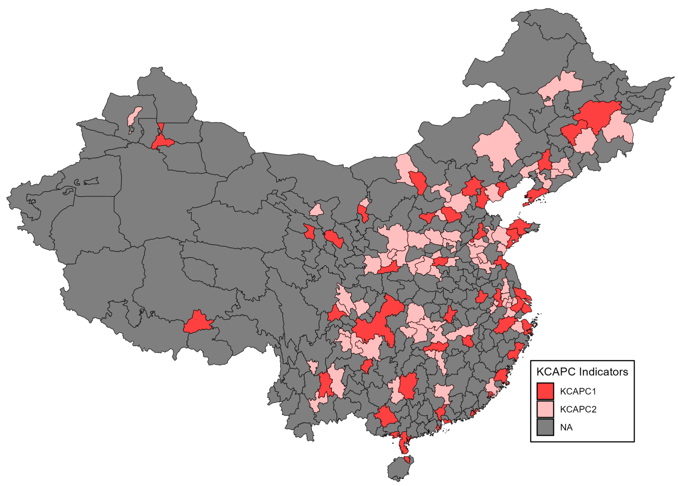
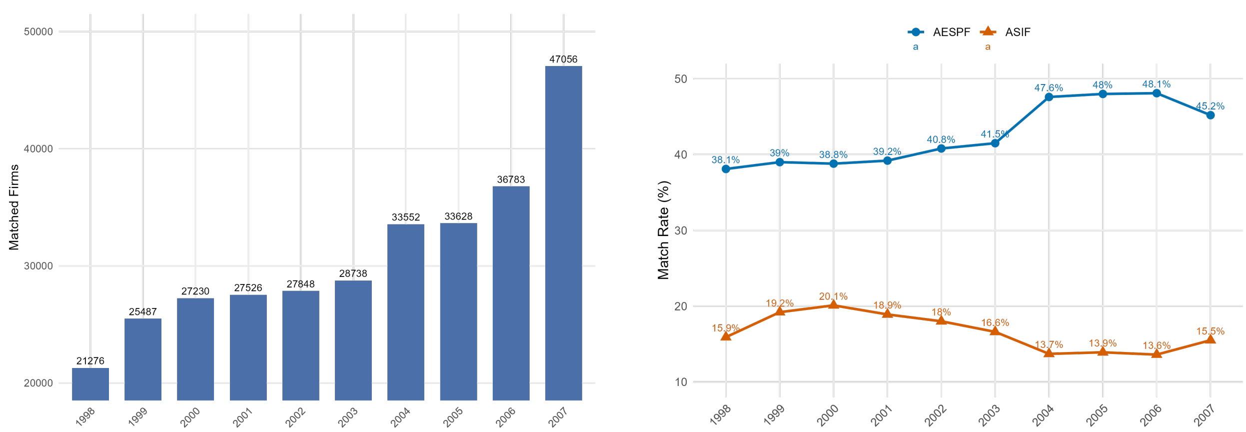


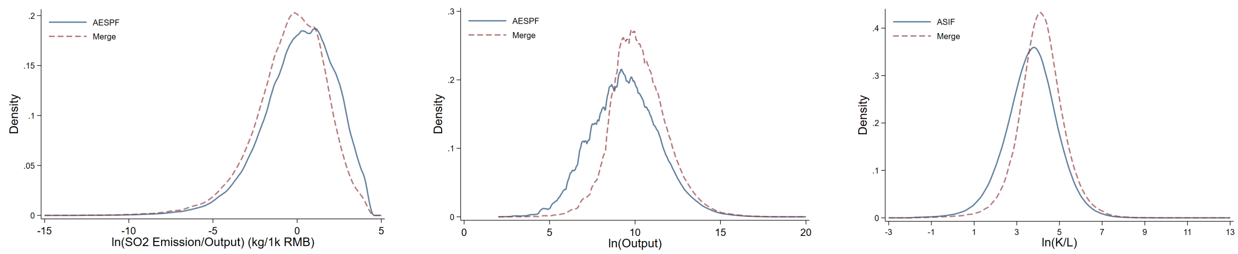
Figure 2: Merge results for ASIF and AESPF



(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)

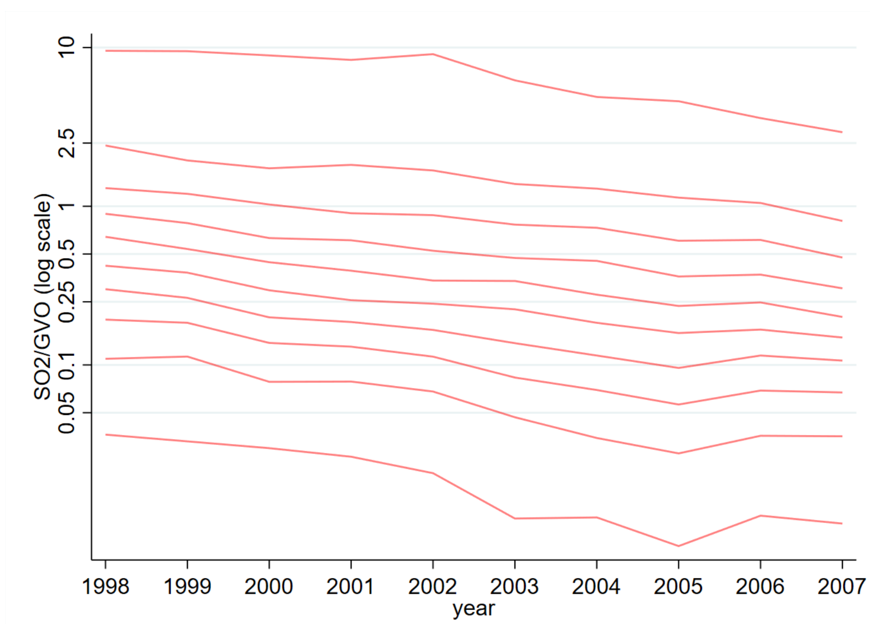


Figure 5: Map of Cities by Treatment Status

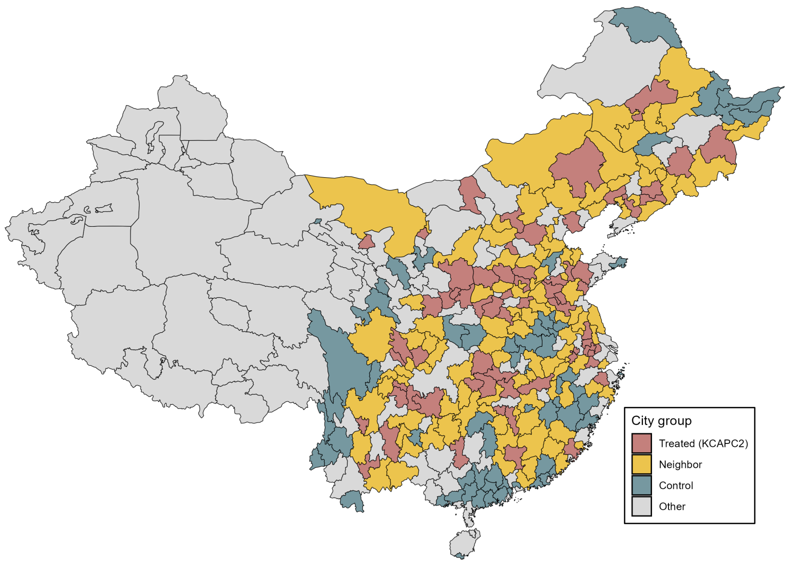
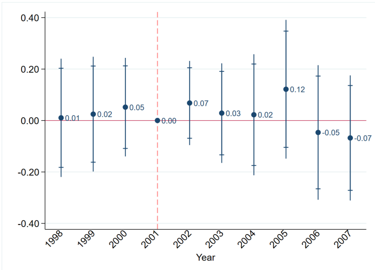
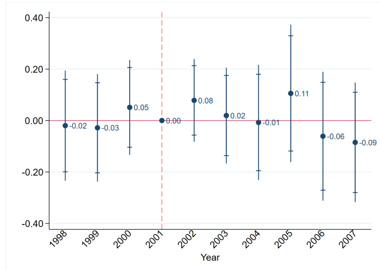


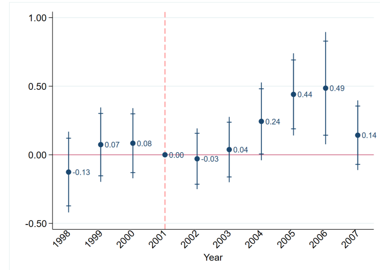
Figure 6: Pre-trend for Aggregate Effects in Neighbor Cities



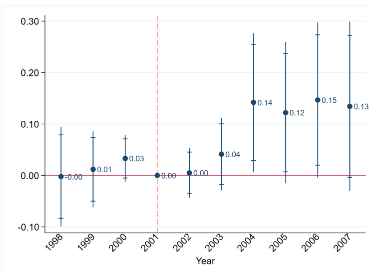
(a) SO_2 Emission Intensity



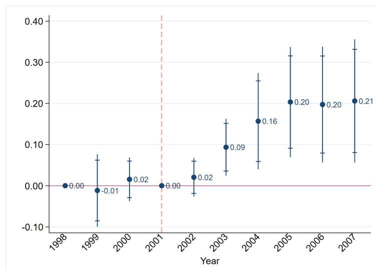
(b) SO_2 Generation Intensity



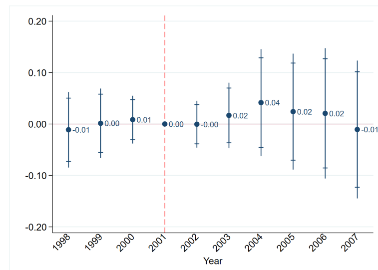
(c) Total SO_2 Emission



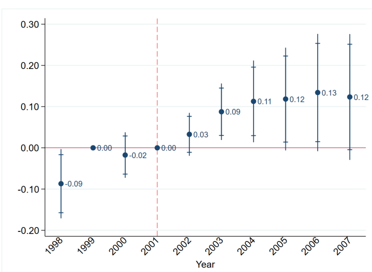
(d) Nfirms



(e) Output



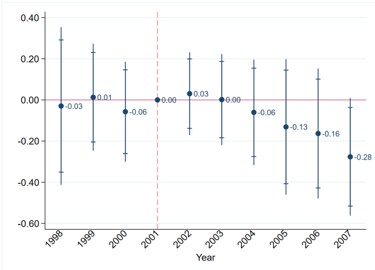
(f) Employment



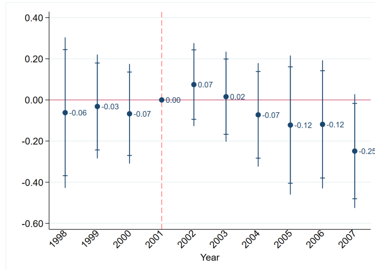
(g) Capital Stock

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

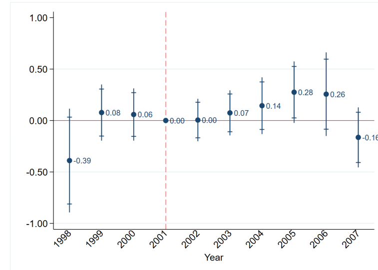
Figure 7: Pre-trend for Aggregate Effects in Treated Cities



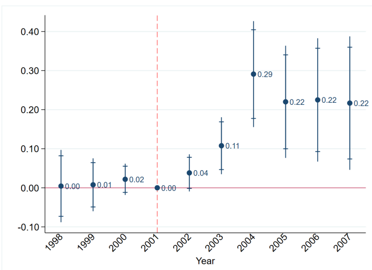
(a) SO_2 Emission Intensity



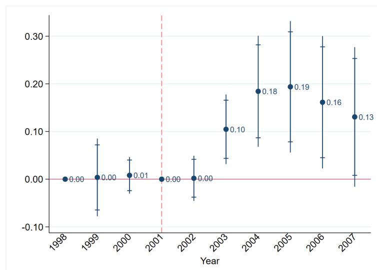
(b) SO_2 Generation Intensity



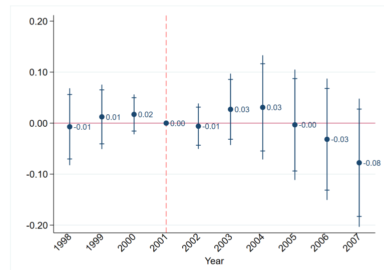
(c) Total SO_2 Emission



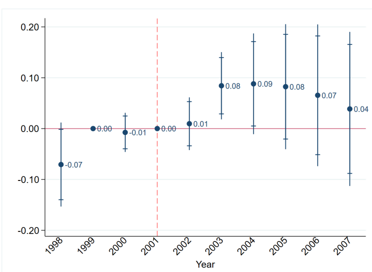
(d) Nfirms



(e) Output



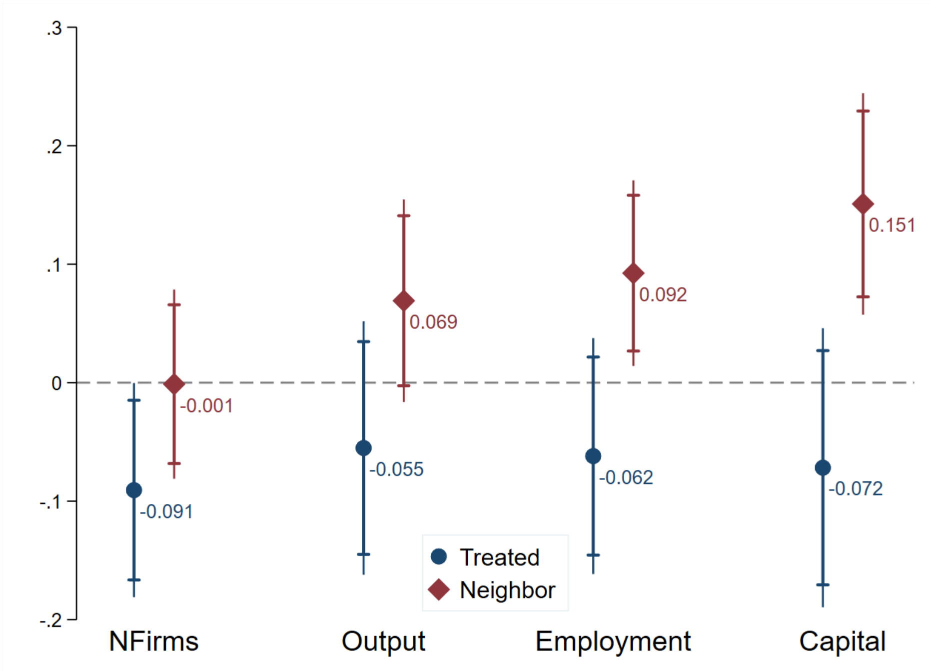
(f) Employment



(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
$\mathbb{1}\{T\} \times$ Post	0.029	0.090
	(0.878)	(0.545)
Pol $\times$ Post	-0.061	-0.060
	(0.683)	(0.682)
$\mathbb{1}\{T\} \times$ Post $\times$ 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)
	$\ln(\text{SO2e}_{\text{tot}})$	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)
	$\ln(\text{SO2e}_{\text{tot}})$	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.

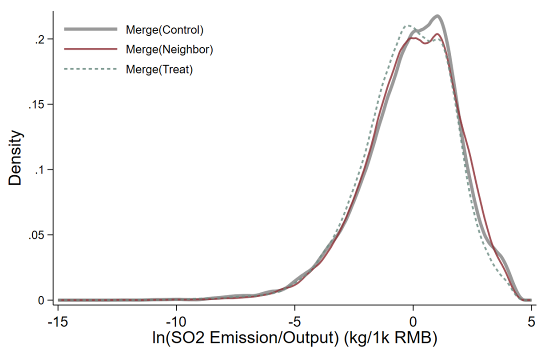
Table B10: Effects on Cross-Province Neighbor Cities

	SO2 Outcomes			Economic Outcomes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln($SO2e_{tot}$)	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

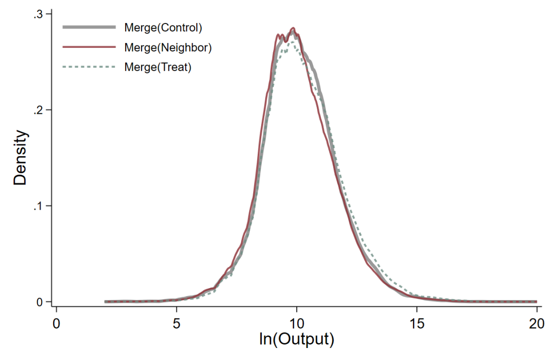
Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

C Additional Figures

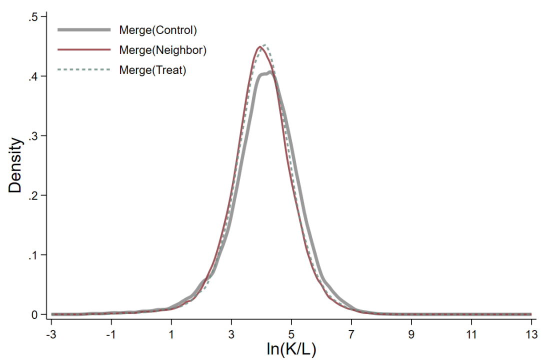
Figure C1: Distribution of Key Stats by Treatment Groups



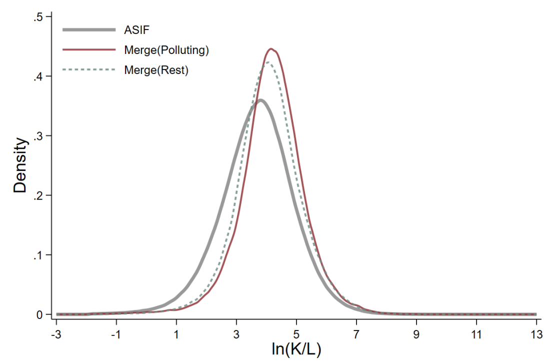
(a) Emission Intensity (by Region)



(b) Output (by Region)



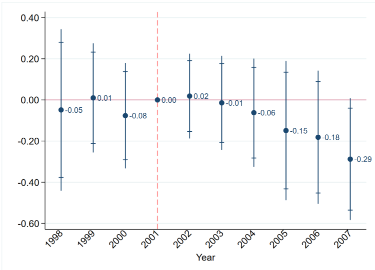
(c) K/L (by Region)



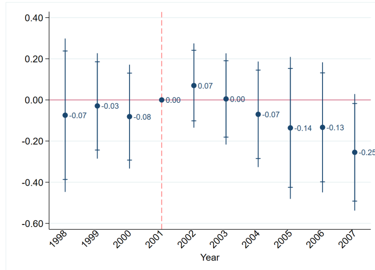
(d) K/L (by Sector)

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.

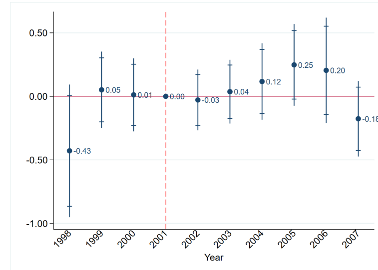
Figure C2: Pre-trend for Aggregate Effects in Treated Cities (Raw DID)



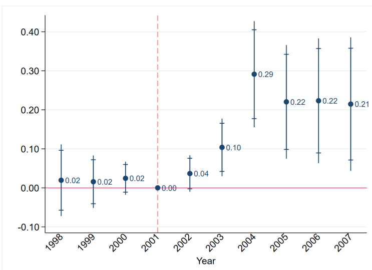
(a) SO_2 Emission Intensity



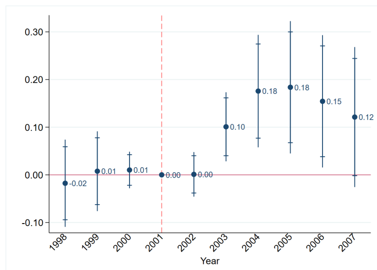
(b) SO_2 Generation Intensity



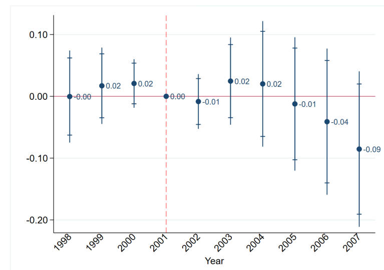
(c) Total SO_2 Emission



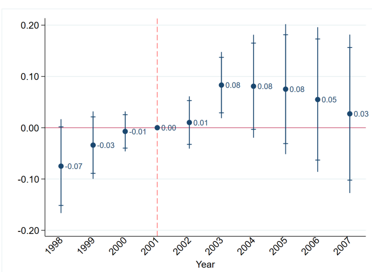
(d) Nfirms



(e) Output



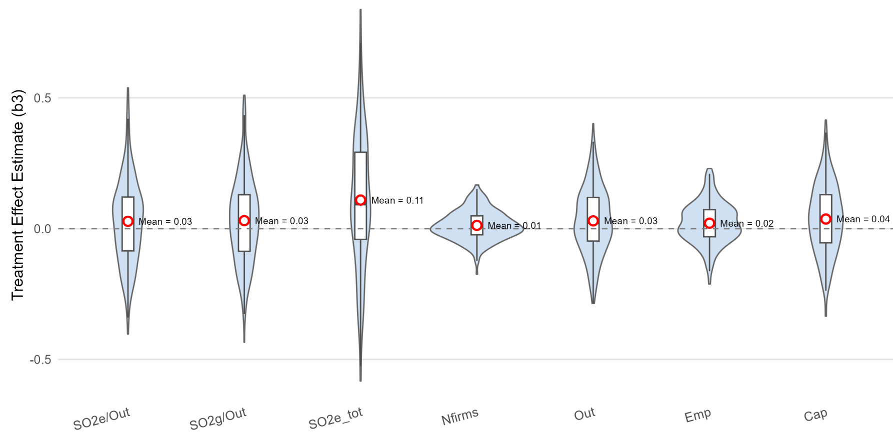
(f) Employment



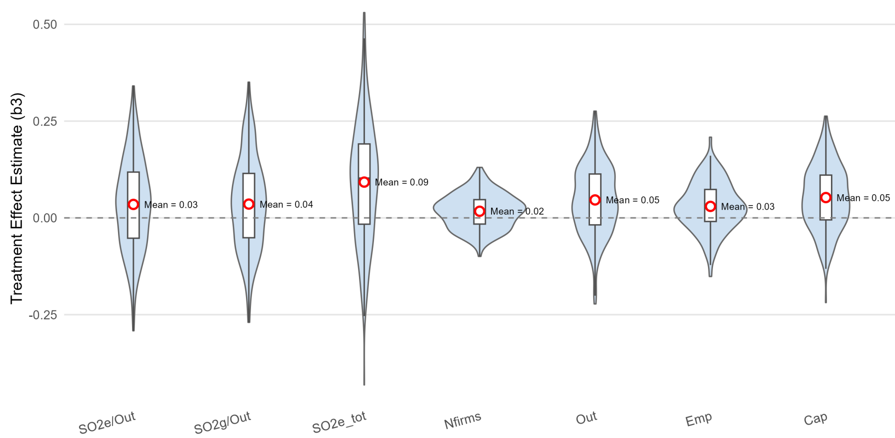
(g) Capital Stock

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



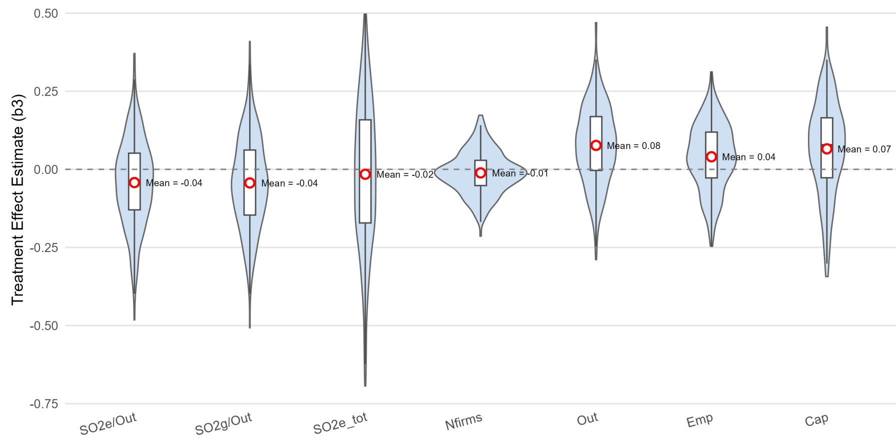
(a) Treated Cities



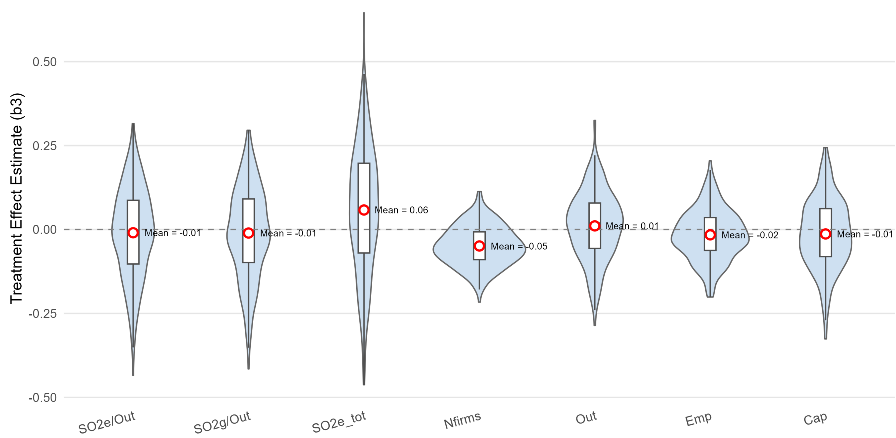
(b) Neighboring Cities

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



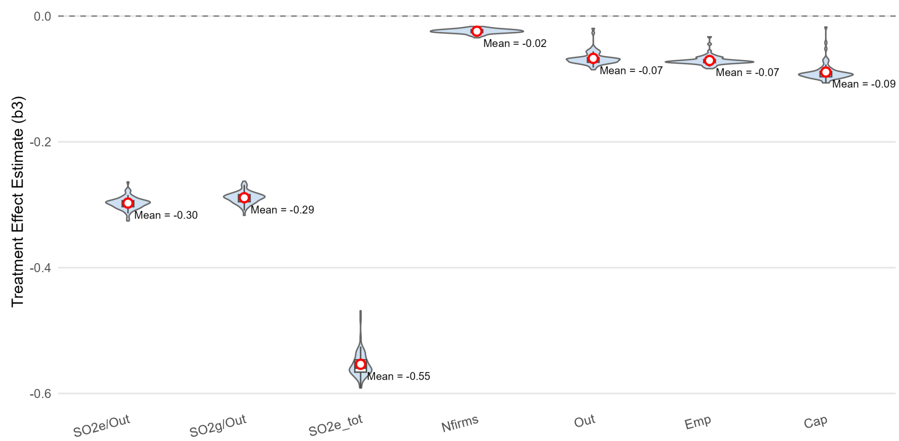
(a) Treated Cities



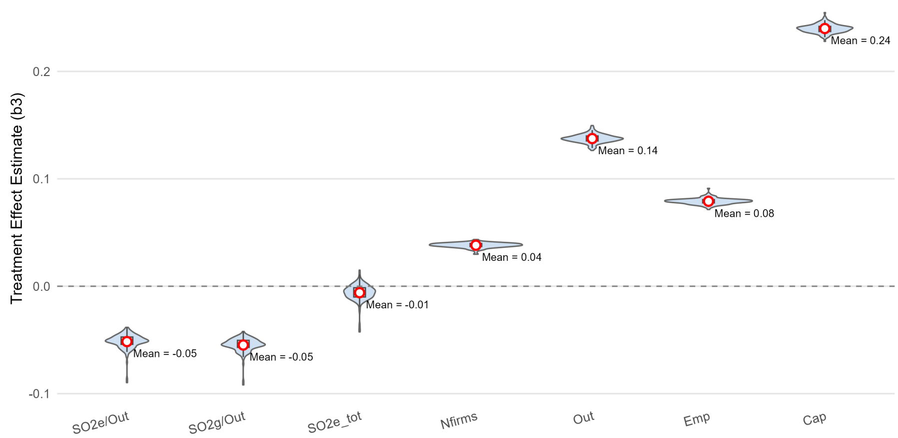
(b) Neighboring Cities

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



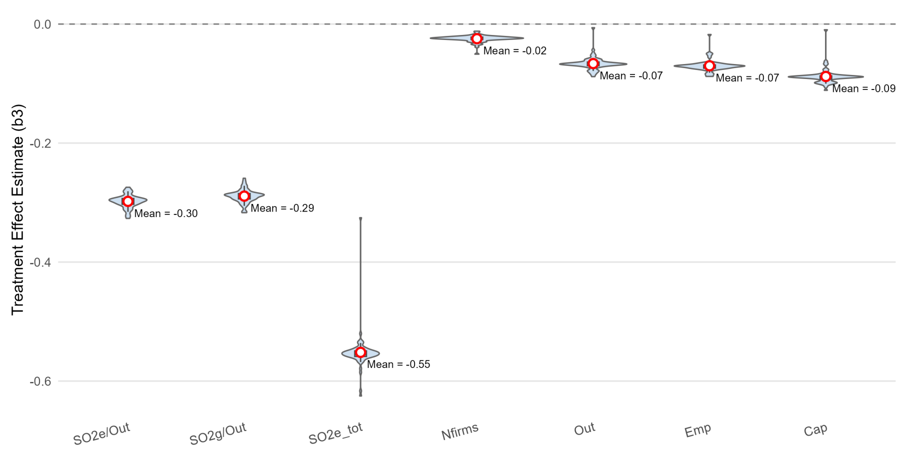
(a) Treated Cities



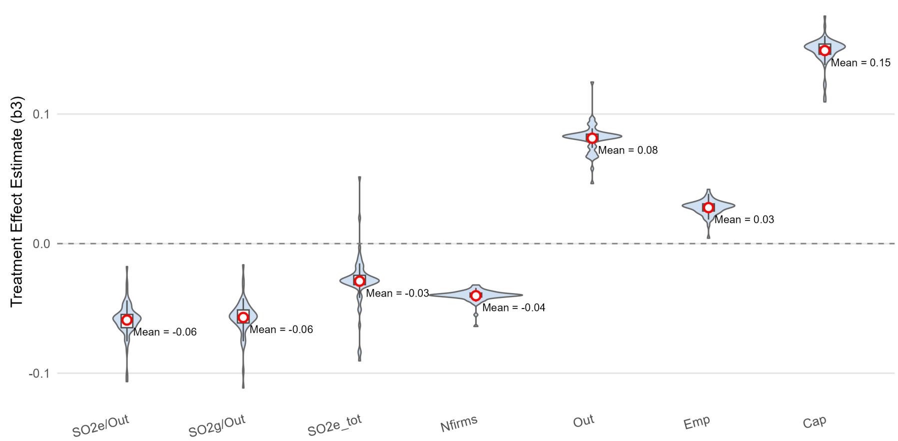
(b) Neighboring Cities

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



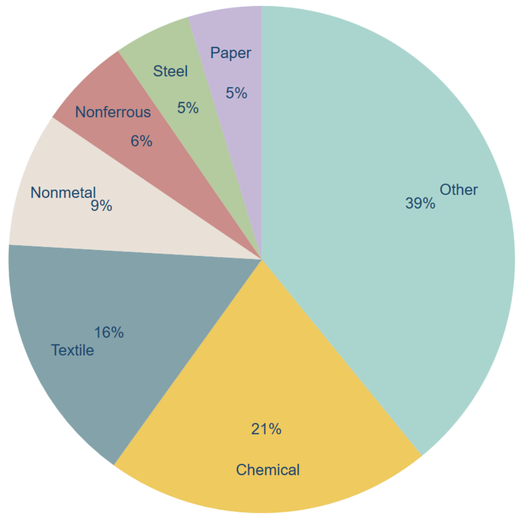
(a) Treated Cities



(b) Neighboring Cities

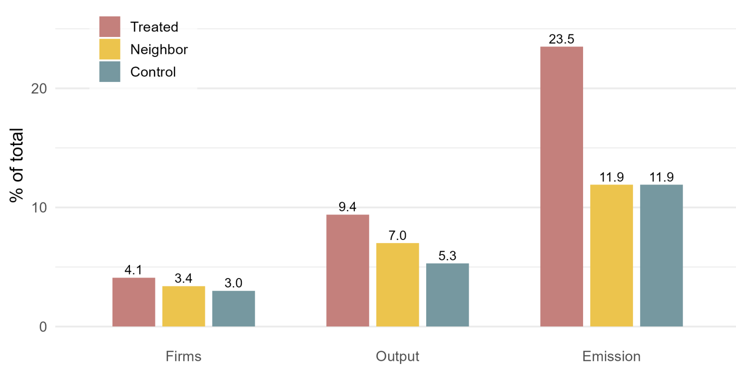
Note: Blue area represents density of distribution for the $\hat{\beta}_3$, red circle represents the mean across all leave-one-out replications, and white box represents range within one standard-deviation of the distribution. Figure a is for the distributions of $\hat{\beta}_3$ for treated cities,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



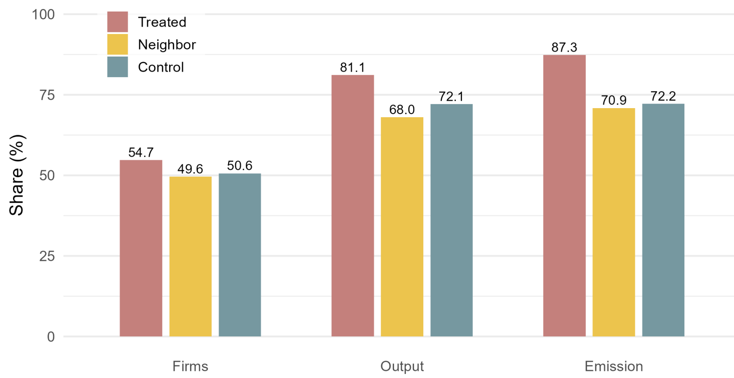
Notes: The pie chart shows the share of two-digit sectors among all switching firms; for example, about 21 % of switching firms are in chemical sectors.

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.