Pollution Haven Next Door: Evidence from China

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Abstract

The Pollution Haven Hypothesis (PHH) posits that regions with weaker environmental regulation will export the pollution-intensive goods. This paper revisits the PHH by investigating the effects of the Key Cities Air Pollution Control (KCAPC) policy, a regional air quality program in China. Using a synthetic difference-in-differences (SDID) design to address non-random selection in treated cities and their neighbors, I analyze how the policy affects both SO_2 outcomes and industrial composition across cities. The findings support the PHH at the regional level: Treated cities shift the source of pollution toward less pollution-intensive sectors, while neighboring cities experience growth in output and capital in pollution-intensive sectors. Further evidence suggests that these patterns are partly explained by strategic production reallocation by local governments via state-owned enterprises (SOEs), as well as firm-level shifts toward cleaner product lines. These findings underscore the importance of spatial context in evaluating environmental regulation and highlight how well-intentioned policies can reshape regional industrial structure in unintended ways.

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

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

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1 Motivation and Introduction

Environmental regulations are often designed within political boundaries, but their economic and environmental consequences rarely stop at the border. As a result, the spatial challenges of environmental regulation have become increasingly salient in both public discourse and academic research (Balboni and Shapiro, 2025). A central concern is the Pollution Haven Hypothesis (PHH), which states that environmental regulation is strong enough to affect industrial structure, either through shifts in production across regions (Hanna, 2010; Copeland et al., 2022; Chen et al., 2025) or through changes in firms' location choices (Henderson, 1995; Harrison et al., 2015). Understanding this interaction between environmental policy and the spatial distribution of economic activity poses a key dilemma for policymakers. Investigating this relationship across different regional contexts has both policy relevance and broader implications for the economic geography of environmental regulation.

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

This paper revisits the PHH in a subnational context, asking whether environmental regulation can reshape the industrial composition of cities within the same national economy. Using China as a case study, I examine the impact of the Key Cities for Air Pollution Control (KCAPC) program, a regional air quality policy, on the relative performance of polluting and less-polluting sectors in both regulated cities and their neighbors. This setting allows me to answer the following questions: (i) Does regional environmental regulation induce shifts in industrial structure consistent with the PHH? (ii) Through what mechanisms do these changes occur?

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 from international trade costs or stark institutional differences. This helps isolate potential reasons why the PHH may not emerge at the cross-country level. Third, China's centralized political structure and performance-based promotion system, where local officials are primarily evaluated on economic outcomes, create strong incentives for selective enforcement or circumvention of environmental policy. The trade-off between environmental quality and economic development is a common dilemma in developing countries, and the Chinese case offers insights into how these dynamics unfold in practice. Taken together, these features make China a particularly informative context for studying the regional mechanisms of the PHH.

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

The analysis draws on two main firm-level datasets: the Annual Environmental Survey of Polluting Firms (AESPF) and the Annual Survey of Industrial Firms (ASIF). The AESPF, conducted by the Ministry of Environment, covers firms responsible for the top 85% of county-level emissions and reports detailed pollutant data, including SO_2 emissions. The ASIF includes all state-owned firms and non-state-owned firms with annual revenues above

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

5 million RMB, providing comprehensive financial, operational, and locational data. Merging these datasets yields a city-sector panel from 1998–2007 for evaluating the KCAPC's effects on environmental performance, industrial composition, and economic structure.

To estimate causal impacts, I apply the synthetic difference-in-differences (SDID) method proposed by Arkhangelsky et al. (2021), which combines synthetic control and difference-in-differences to address non-random treatment selection and heterogeneous pre-trends. I examine both aggregate effects and heterogeneous impacts across sectors, distinguishing between the top-quintile most pollution-intensive industries (ranked by SO_2 intensity) and less-polluting industries. To provide further evidence for the PHH, I also investigate changes in neighboring, non-treated cities. In both analyses, I construct the control group from distant, non-neighboring cities.

This choice is important theoretically and empirically: neighboring areas are likely exposed to policy-induced spillovers via the PHH channel, so including them as controls would bias estimated treatment effects downward. By excluding potentially contaminated neighbors, my research design reduces bias in the estimated effects for treated cities. Moreover, analyzing neighboring cities separately allows me to test whether spatial spillovers operate through the PHH channel directly. In this way, the approach complements prior firm-level studies of KCAPC (Liu et al., 2021; Viard et al., 2022) that rely on geographically proximate controls and helps reconcile differences in findings.

Using this framework, I find evidence supporting the PHH in both treated cities and their neighboring areas. In treated cities, the KCAPC reduces emission intensity in top-quintile polluting sectors and shifts SO_2 emissions toward less-polluting sectors. In terms of economic outcomes, I observe a substantial increase in output for less polluting sectors and a more modest increase for polluting sectors. However, there is no significant effect on differential growth patterns, suggesting that KCAPC led to a shift in pollution composition rather than a reallocation of economic specialization. The effects are more pronounced in neighboring cities. Compared to distant control cities, neighboring areas experienced significant increases in both total emissions and output, with output growth mainly driven by polluting sectors. My results are robust to different specification checks, such as a placebo test with randomly assigned treatments and sectors, using a different pollutant.

To better understand the mechanisms driving these patterns, I examine whether the observed shifts arise from firm relocation or from adjustments in production among existing firms. The evidence points clearly toward the latter.

First, firms in regulated cities reallocate production toward less pollution-intensive products; excluding such within-firm product shifts substantially attenuates the observed differences in sectoral output. Second, the cross-city reallocation of production is largely driven by state-owned enterprises (SOEs), which expand in cleaner sectors within treated cities and in more polluting sectors in neighboring cities. In contrast, the corresponding effects for non-SOEs are small and statistically insignificant. Finally, while there is some evidence of higher exit and lower net entry in treated polluting sectors, these effects are quantitatively small, suggesting that firm entry or exit plays only a minor role. Taken together, these results indicate that the KCAPC policy induced reallocation primarily through adjustments by incumbent firms (particularly SOEs) rather than through firm relocation or new entry.

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

This paper contributes to the extensive literature on the Pollution Haven Hypothesis and the broader issue of environmental regulation leakage (Antweiler et al., 2001; Barrows and

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

Ollivier, 2021; Duan et al., 2021; Levinson, 2009, 2023; Tanaka et al., 2022). See Copeland et al. (2022) for a detailed review. Most existing studies focus on cross-country analyses comparing the global North and South, generally finding limited evidence supporting the PHH. Particularly, existing papers find that trade-induced changes in pollution mostly stem from the change in overall output (Barrows and Ollivier, 2021), or pollution intensity (Cherniwchan, 2017; Holladay, 2016; Najjar and Cherniwchan, 2021; Shapiro and Walker, 2018), instead of industrial structure. Research examining the PHH within a single economy primarily relies on conditional logit models (Wu et al., 2017; Wang et al., 2019; Yang et al., 2018), which pose limitations for causal inference and policy evaluation. In contrast, this paper investigates a less-studied spatial context at the city level and is among the first to provide causal evidence that is consistent with the PHH. Using the KCAPC policy as a case study, I demonstrate that treated cities tend to specialize more in less-polluting industries, while neighboring cities experience a relative increase in specialization in polluting sectors.

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 (Curtis et al., 2025; 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, 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. Another paper worth mentioning is Curtis et al. (2025), which finds roughly half of the reduced employment due to CAA is attributed to leakage to unregulated regions within multi-unit firms, using an event study design and weighted distance. Compared to their study period of around two decades, this paper shows that the shift in production can happen within a short period (2002-2007) through various channels.

Finally, this paper contributes to the literature on heterogeneous environmental regulation stringency and the principal-agent problem in environmental governance. Prior research documents that local governments in developing countries often face weak institutions or prioritize economic growth (Duflo et al., 2013; Du and Li, 2023), which can lead to uneven enforcement of environmental regulations across regions. A related strand of literature shows that environmental regulations tend to be more lenient in border areas (Cai et al., 2016; Lipscomb and Mobarak, 2016; Monogan III et al., 2017). This study further identifies that firms with stronger ties to local governments play a key role in circumventing regulation. Specifically, I find that SOEs tend to expand more in less-polluting sectors within regulated cities, while expanding more in polluting sectors in neighboring non-regulated areas. These findings differ from those in Chen et al. (2018), who document local governments trading off economic mandates for environmental performance. The divergence may stem from the fact that my analysis focuses on a period when economic growth was more heavily prioritized.

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

2 Policy Background

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

The KCAPC policy was first launched in 1998 and expanded later with the objective of improving air quality in key urban areas. The central government initially designated 47 prefecture-level cities — primarily provincial capitals, special economic zones, and major tourist destinations — as the first batch of targeted cities. A second batch of 66 additional cities was designated in December 2002 under the Tenth Five-Year Plan.[4] These cities were required to meet specific air quality targets by 2005, based on China's Class II Air Quality Standard (GB3095-2000) for SO_2 and five other pollutants.

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

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

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

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

industrial emitters and areas with higher administrative capacity.

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

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

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

Additionally, KCAPC policy targeted certain polluting industries more aggressively than others, as outlined in the Tenth Five-Year Plan. The plan emphasized controlling pollution from key sectors such as metallurgy, petrochemicals, cement, paper products, and the

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

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

textile industry. In a subsequent review report,[8] the government highlighted efforts to promote technological upgrades in these industries, claiming that total output in these sectors continued to grow while their pollution intensity declined.

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

3 Data

3.1 Annual Survey of Industrial Firms

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

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

Using the cleaned dataset, I construct measures of total gross sales revenue, capital stock,

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

employment, and the number of firms at the city-sector-year level. I also use the average wage to control for potential differences in labor cost.

3.2 Annual Environmental Survey of Polluting Firms

The Annual Environmental Survey of Polluting Firms (AESPF)[9] is the most comprehensive firm-level environmental dataset available in China. Conducted by the Ministry of Environment, the survey provides detailed information on firms' environmental performance, including emissions of major pollutants, use of pollution abatement equipment, and energy consumption. Key pollutants include SO_2, the primary focus of the KCAPC and this paper, as well as chemical oxygen demand (COD), ammonia nitrogen, industrial smoke, dust, and solid waste.

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

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

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

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

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

3.3 Other Data Sources

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

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

3.4 Merging Datasets

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

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

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

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

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

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

4 Empirical Strategy

4.1 Synthetic Difference-in-Difference

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

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

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

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

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

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. $KCAPC_c$ 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:

$$ln(Y_{sct}) = \alpha + \beta_1 KCAPC_c \times Post_t + \beta_2 Pollute_s \times Post_t + \beta_3 KCAPC_c \times Post_t \times Pollute_s + \sigma_{sc} + \tau_t + \epsilon_{sct} \tag{2}$$

Here, I further separate outcomes within a city between the top quintile sectors in terms of polluting intensity and the rest, see Section 4.2 for a detailed explanation. In this model, Y_{sct} is the outcome for the aggregate sector s in city c at year t. $Pollute_s$ is a dummy that equals 1 for the sector of top quintile pollution intensity in 1998. I include city-sector fixed effects to account for variation such as heterogeneity in baseline industrial composition across cities. If KCAPC alters the economic structure as expected, $\hat{\beta}_3$ should be negative.

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

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

4.2 Defining Polluting Sectors and Descriptive Statistics

The SDID framework allows me to estimate both aggregate and heterogeneous treatment effects. To examine heterogeneity, I need to operationalize which industries are "polluting" and which are "less-polluting." As noted in Section 3.4, the merged dataset is skewed toward larger firms and polluting sectors, but what matters for the empirical analysis is the **relative**

ranking of sectoral pollution intensity. In what follows, I describe how I construct this ranking and classify industries into top-quintile polluting sectors and the remainder, and I show evidence and robustness checks that support such classification.

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

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

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

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

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

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

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

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.

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

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

$$match_{sct} = \alpha + \beta_1 KCAPC_c + \beta_2 Nb_c + \tau_t + \sigma_s + \epsilon_{sct}, \tag{3}$$

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

Second, I compare the firm-level distributions of emission intensity, output, and capital–labor ratios across treatment groups (Figure C1). These distributions are similar between treated, neighboring, and control cities, indicating that the merged dataset does not disproportionately represent certain types of firms in any particular group. Taken together, these results suggest that the skew in the merged sample does not vary systematically across treatment groups and therefore is unlikely to bias the estimated policy effects.

5 Results on Treated and Neighboring Cities

5.1 Effect of KCAPC on Targeted Cities

I begin by examining the average effect of the KCAPC policy on a range of city-level outcomes. To assess dynamic treatment effects and test for pre-trends, I estimate the event study version of Equation (1). The resulting point estimates are plotted in Figure 5. The estimates show no statistically significant pre-trends prior to the policy's implementation in 2002, which supports the credibility of the identification strategy. The post-treatment coefficients do not indicate a consistent or statistically significant decline in either economic activity or environmental outcomes. In fact, there is no clear negative trend in total SO_2 emissions or economic indicators following the policy.

Panel A of Table 6 reports the average treatment effects at the city level. The point estimate for SO_2 emissions and generation per unit of output are negative, while the estimates for total SO_2 emissions is positive. However, none of these coefficients are statistically significant, and therefore no firm conclusions can be drawn regarding the policy's effect on environmental outcomes.

Columns 4 through 7 of Table 6 present the estimated effects on economic outcomes. The KCAPC policy is associated with a statistically significant 13.4 percent increase in total output. This appears to be driven by a 19.5 percent increase in the number of firms, indicating that average firm size may have declined. 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 further examine how the KCAPC policy affected the economic and environmental structure of treated cities, I estimate Equation (2), and report the results in Panel B of Table 6. Column 1 presents the estimates for SO_2 emission intensity. The coefficient for less-polluting sectors is positive but statistically insignificant, while the estimate for polluting sectors shows a significant 18.9 percent reduction in emission intensity. The coefficient in Column 2 shows that emissions generated per unit of output decline by 16.4 percent, suggesting that approximately 86.8 percent of the intensity reduction is attributable to cleaner production processes rather than end-of-pipe abatement technologies.

Column 3 reports the effects on total SO_2 emissions. The results indicate that emissions in polluting sectors declined by 10.7 percent, while emissions in less-polluting sectors increased by 55 percent. Based on the fact that 73.3 percent of baseline SO_2 emissions come from top-quintile polluting sectors, the implied overall change in emissions is approximately a 6.8 percent increase, slightly smaller than the aggregate estimate from the city-level model.

The increase in SO_2 emissions from less-polluting sectors appears to be partly driven by an expansion in output, as shown in Column 5. However, output in these sectors rose by only 15.3 percent, compared to a 55 percent increase in emissions. This suggests that the additional production was significantly more pollution-intensive than before. This raises an important question: why do emissions rise in cleaner sectors, despite regulation targeting polluting sectors? As I will show in Section 6.1, this pattern is likely explained by firms in polluting sectors shifting toward less pollution-intensive product lines.

At the same time, point estimates in Columns 6 and 7 indicate that less-polluting sectors became more capital-intensive following the policy, with capital stock increasing disproportionately relative to employment. The expansion in output is largely driven by the extensive margin, as the number of firms in less-polluting sectors rose by 19.9 percent.

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

Overall, the results suggest that at the city level, the KCAPC policy primarily affected top-quintile polluting sectors and led to a shift in the source of emissions from these highly polluting industries toward relatively cleaner sectors. In terms of economic outcomes, I find that output grew significantly in less-polluting sectors, while growth in polluting sectors was more modest. However, although the coefficients for triple-difference indicators are negative, they are all insignificant, which is not strong enough to conclude that the policy induced a meaningful shift in economic specialization across sectors. Later in Table B5 of Section 5.5, I show that KCAPC results in a significant drop in the share of SO_2 emission, but a modest and insignificant drop in other economic outcomes. Taken together, these results imply that there was a shift in pollution composition rather than economic specialization.

These findings differ from prior firm-level studies of the KCAPC policy, such as Liu et al. (2021) and Viard et al. (2022), which report significant reductions in firm-level emissions.

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

5.2 Effect of KCAPC on Neighboring Cities

The previous section presents evidence that the top quintile polluting sectors in treated cities observe a drop in the share of SO_2 emissions. However, this alone is not sufficient to establish the presence of a Pollution Haven Hypothesis (PHH) operating across cities in China due to the KCAPC policy. A key empirical implication of the Pollution Haven Hypothesis is that regulatory stringency in one area leads to a shift of pollution-intensive production to less-regulated areas nearby. To verify this mechanism, I examine whether neighboring, non-regulated cities begin to specialize in pollution-intensive activities following the policy.

This second strand of analysis focuses on non-treated cities that share a border with treated cities. I begin by estimating the aggregate effects of the policy at the city level. Panel A of Table 7 presents the results. Column 3 shows that, compared to distant control cities, neighboring cities experienced a statistically significant increase in total SO_2 emissions. Columns 1, 2, and 5 indicate that the rise in emissions is driven primarily by higher total output, rather than by an increase in pollution intensity. Overall, these cities saw a 20.7 percent rise in SO_2 emissions, a 16.2 percent increase in output, and a 12 percent rise in capital stock. The corresponding event study plot in Figure 6 shows pre-trends for different outcome variables.

Panel B of Table 7 reports results by sector pollution intensity. The largest changes are observed in the top quintile of polluting sectors. Column 5 shows that the increase in total output is driven by these pollution-intensive sectors. Unlike the extensive-margin expansion seen in treated cities, this output growth appears to be primarily driven by the intensive margin: the point estimates for the number of firms are small and statistically insignificant. Column 7 shows a similar pattern for capital stock.

These findings suggest that neighboring cities increasingly specialize in pollution-intensive activities. However, Column 1 shows no statistically significant difference in total SO_2 emissions between polluting and less-polluting sectors. This may be due to a combination of factors: increased output in less-polluting sectors and potential reductions in emission intensity within polluting sectors. Columns 1 and 5 support this interpretation, although these estimates are not statistically significant. Later in Table B5 of Section 5.5, I show that neighboring cities observe an increase in the share of emissions and economic outcomes for polluting sectors.

The overall sector-specific effects are as follows. In less-polluting sectors, the number of firms rose by 6.7 percent, output by 6.8 percent, and capital stock declined by 1.8 percent. In contrast, top-quintile polluting sectors experienced a 10.9 percent increase in the number of firms (not statistically significant), a 22.7 percent increase in output, and a 24.9 percent increase in capital stock.

5.3 Location Quotient Analysis

The treated and neighbor results suggest that the KCAPC policy reshaped the sectoral composition of output and emissions in ways consistent with the PHH. To further validate this interpretation, I examine changes in regional industrial specialization using the Location Quotient (LQ) index. The LQ is a standard measure of relative specialization in agglomeration literature, defined as the ratio of a sector's share of activity in a city to its share at the national level.[11] An LQ above one indicates that a city is more specialized in that sector than the national average, while an LQ below one indicates less specialization.

While LQ provides an intuitive measure of specialization, absolute changes in LQ are not directly comparable across outcomes (firms, output, employment, capital) or over time. A shift of 0.1 in LQ may represent a meaningful change in one context but be negligible in another, depending on baseline variation. To facilitate comparability of effects across outcomes, I standardize the index within each year and sector to obtain a z-score measure (zLQ).[12] 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:

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

Where zLQ_{ct} are standardized LQ for polluting sectors in targeted cities, and 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 95% confidence intervals in Figure 7. The results show that treated cities experience a relative decline in LQ for polluting sectors, whereas neighboring cities see an increase, consistent with PHH. This additional evidence reinforces the baseline findings and complements the sector-level regression analysis.

5.4 Discussion

In summary, the evidence from both treated cities and their neighboring regions suggests that the KCAPC policy primarily targets and affects top-quintile polluting sectors, but its overall effectiveness is limited. While the policy reduces both total SO_2 emissions and emission

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

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

intensity within polluting sectors of treated cities, the net city-level effect on emissions is positive, albeit statistically insignificant. At the same time, neighboring cities experience a significant increase in emissions driven by growth in polluting sectors.

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

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

5.5 Robustness Check

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

5.5.1 Other Pollutant

First, I check the effect of the KCAPC policy on water pollution instead. China started various environmental regulation programs during my study period. Hence, it is possible that KCAPC coincides with other programs that target another source of pollution, i.e., water pollution. To verify that KCAPC policy's SO_2 regulation indeed drives the results, I estimate the policy effect on chemical oxygen demand (COD)[13] in Table B2 as a robustness check. The coefficients are all small and insignificant. The absence of similar patterns for COD confirms that observed shifts are pollutant-specific to SO_2 regulation.

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

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[14] as treated 250 times and re-estimate the SDID specification. Figure C2 plots the distribution of $\hat{\beta}_3$ ($KCAPC \times Post \times Pol$) across these simulations. If the KCAPC policy truly drives the observed effects, the placebo distributions should be centered around zero, with no systematic negative effects for "treated" cities or positive effects for their neighbors. Consistent with this expectation, the simulated mean distributions are all close to zero and differ markedly from the baseline estimates. The only exception is a larger dispersion for total SO_2 emissions, likely reflecting the skew 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[15] as "treated" polluting sectors 250 times and re-estimate the SDID specification. Figure C3 shows the resulting distribution of $\hat{\beta}_3$ ($KCAPC \times Post \times Pol$). 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

[14] Consistent with the actual number of treated cities after excluding three western provinces.
[15] This number matches the actual count of top-quintile polluting sectors out of 308.

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 $\hat{\beta}_3$ ($KCAPC \times Post \times Pol$). 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 C4 shows that the treated-city LOO distributions are tightly centered on the baseline coefficients with limited dispersion. $\hat{\beta}_3$ remains negative throughout. The corresponding neighbor LOO distributions (Figure b) are also centered on the baseline. These patterns indicate that no single city drives the main results.

Second, I perform an analogous LOO exercise at the sector level, dropping one of the 61 top-quintile sectors in turn and re-estimating the model. Figure C5 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 B3 and Table B4, 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 Change in Sector Share

Finally, I examine changes in the share of SO_2 emissions and economic outcomes accounted for by top-quintile polluting sectors at the city level. The results, reported in Table B5, show that treated cities experience a significant decline in the share of total SO_2 emissions, whereas neighboring cities exhibit a significant increase in the share of capital stock.

6 Mechanisms

6.1 Firms Switching Products

Existing literature has documented that firms frequently 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) finds that firms substitute pollution input (i.e., from air emissions to water emissions) in response to the cost change due to regulation. Therefore, it is natural to expect firms to mitigate regulatory costs by shifting toward less pollution-intensive products or sectors, especially when policy targets are sector-specific. In what follows, I find that KCAPC induced a reallocation of production toward less-polluting sectors within treated cities, with switching firms driving roughly 17 % of this shift.

Although the ASIF dataset does not contain detailed product-level information, I do observe that firms are changing their sectors across years, which represents firms' major production category.[16] Using this information, I track firms that switch their principal 4-digit

[16] Based on the National Bureau of Statistics, the classification of a unit into a specific national economic industry should be based on its principal activity. When a unit engages in two or more economic activities, the one that contributes the most to its value added is considered its principal activity. For more details, see Statistical Systems and Classification Standards (17) (in Chinese)

sector over time. In particular, I focus on those that shift from a top-quintile polluting sector to a less-polluting one. I refer to these as switching firms. While changes in sector classification likely reflect shifts in principal production activity, some misclassification cannot be ruled out. Nevertheless, the stylized facts presented below consistently indicate that any residual misclassification is minor and unlikely to drive my results.

First, the firms switching sectors are concentrated in highly polluting industries and largely do so within 2-digit CIC divisions. Figure C6 shows that the 2-digit sectors with the highest frequency of switching are also those that are more pollution-intensive. Moreover, roughly 75 % of switching firms remain within their original 2-digit sector and likely reduce their pollution intensity. For example, chemical producers often move from basic chemicals to organic chemical products; textile firms shift from raw-fiber processing to cotton or wool textiles; and non-metal mineral enterprises switch from cement manufacturing to concrete products.

Second, treated cities have a more salient pattern for switching firms. Table B6 presents the annual share of switching firms and their contribution to total outcomes by treatment group. The data reveal two key patterns. First, switching firms tend to be larger and more polluting on average, as indicated by their disproportionately large shares of total output and SO_2 emissions relative to their share of firms. Second, switching behavior is more prevalent in treated cities than in neighboring or distant control cities. The above patterns suggest that product switching may be an important channel through which firms respond to sector-specific environmental regulation.

To further examine whether firms respond to the KCAPC policy by changing their principal line of production, I estimate the following two equations:

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

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

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 located in treated cities are associated with a higher probability of switching their primary production activity to a less-polluting sector following the policy. Columns 2 through 4 show that, conditional on switching, firms exhibit significantly higher output and capital stock in the post-policy period. These findings are consistent with the idea that switching is a proactive strategy by firms to maintain or enhance performance while adapting to regulatory constraints.

The above results support the claim that firms are switching their major production activities due to KCAPC regulation. Therefore, I restrict the sample to those firms that never switch, and check how treatment effects differ from the results based on the unfiltered dataset, see Column 1 and Column 2 for Table 9.

I begin by examining the effect of the KCAPC policy on treated cities using the subsample of non-switching firms, reported in Panel A. While the triple-difference coefficients remain negative, their magnitudes are small and close to zero. This indicates that most of the differential change between polluting and less-polluting sectors is driven by firms that switch their primary production activity. Since switching firms account for 9.6 percent of total output in less-polluting sectors after the policy is implemented, I estimate that these firms contribute approximately 16.7 percent of the observed increase in output for less-polluting sectors in treated cities.[17]

[17] The contribution of switching firms is calculated as $x = 1 - w \cdot \frac{\beta_{\text{nsw}}}{\beta}$, where w is the output share of non-switching firms (i.e., $1 - 0.096$), β_{nsw} is the coefficient for $KCAPC \times Post$ in Column 2, Panel A, Table 9, and β is the corresponding coefficient in Column 5, Panel B, Table 6.

As for the effect on neighboring cities, the results are reported in Column 1 and 2 of panel B. For consistency, in this context, switching is defined symmetrically as firms moving from less- to more-polluting sectors. It shows that all point estimates are only slightly smaller. This suggests that firms switching their major product is not a driving factor in neighboring cities. One possible explanation is that firms in neighboring cities are not facing pressure like those in the treated regions, and the benefit of switching is not enough to justify the cost.

6.2 SOEs and non SOEs

In this section, I find that State-Owned Enterprises (SOEs)[18] absorbed most of the sectoral adjustment in treated cities and the increase in polluting activity in neighboring cities, indicating their role as policy instruments.

Existing literature has documented that local governments in developing countries often operate under weak institutional constraints or prioritize economic development (Duflo et al., 2013; Jia, 2017; Du and Li, 2023), making them either unable or unwilling to enforce uniform regulations across regions. Consequently, empirical evidence suggests that pollution-intensive firms may concentrate near the borders of regulated regions to minimize regulatory oversight (Lipscomb and Mobarak, 2016; Monogan III et al., 2017; Cai et al., 2016).

This pattern is particularly salient in China, where local governments set aggressive growth targets to demonstrate compliance with central mandates (Chang et al., 2025). This phenomenon, known as *"top-down amplification"*, may come at the cost of environmental protection (Jia, 2017). At the provincial level, governors may therefore have incentives to circumvent regulation by shifting pollution-intensive production to adjacent, non-regulated areas within the same province.

SOEs may serve as a channel through which local governments achieve this objective for

[18] I classify SOEs in my dataset following Hsieh and Song (2015). Particularly, a firm is identified as SOE if it is classified as state-controlled directly in the dataset or if the share of registered capital held directly by the state exceeds or equals 50 percent.

the following reasons.

First, SOEs constitute a substantial share of the local economy, particularly in polluting sectors. Table B7 reports the annual fraction of SOEs by number of firms, output, and SO_2 emissions for all sectors, while Table B8 report those statistics for polluting sectors only. Table B7 shows that, while treated regions show broadly similar initial SOE shares compared to other regions, these shares decline more slowly over time. Additionally, the statistics in Table B8 show that SOEs have a higher share in polluting sectors.

Second, SOEs are expected to facilitate the local government in fulfilling policy targets (Berkowitz et al., 2017). Local governments in China possess considerable authority over SOEs, including participation in managerial decisions and the power to appoint key executives.[19] In Table B9, I report the share of SOEs that are not privatized. The table shows that despite a similar share among different cities in 1998, non-privatized SOEs account for a much higher share in output and emissions as time elapses. The above patterns are consistent with the notion that local governments in treated cities maintain a stronger reliance on SOEs, potentially using them as policy instruments to buffer against the adverse economic impacts of environmental regulation.

In what follows, I restrict the sample to SOEs[20] and non-SOEs, respectively, and re-estimate the effects of the KCAPC policy. The results are presented in Columns 3 through 6 of Table 9.

In treated regions, the results indicate that SOEs are the primary drivers of the observed difference in policy effects between polluting and less-polluting sectors. As shown in Column 4 of Panel A, output in less-polluting sectors expands by 0.495, compared to a smaller combined effect of 0.207 in polluting sectors. This difference is partly attributable to changes in the number of firms, as Column 3 shows a similar pattern. By contrast, the estimates

[19] 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).

[20] The SOEs here refer to all firms that have ever been SOEs, this is due to the concern that firms may stay connected with the government even after they are privatized.

for non-SOEs in Columns 5 and 6 are small, statistically insignificant, and show a negligible difference between polluting and less-polluting sectors. Taken together, these results support the interpretation that local governments leverage SOEs to absorb the impact of environmental regulation. As a result, SOEs account for 78 percent[21] of the observed increase in output in less-polluting sectors.

In neighboring cities, the results in Panel B reveal a different pattern. SOEs exhibit significant growth in polluting sectors, while non-SOEs show increases in both polluting and less-polluting sectors. This suggests that SOEs may play a more prominent role in absorbing polluting activities displaced from regulated cities.

The results above suggest that the heterogeneous treatment effects between polluting and less-polluting sectors are largely driven by SOEs. The increasing presence of SOEs in treated regions may partly explain why non-SOEs are more likely to relocate to neighboring cities. This interpretation is supported by the significant increase in the number of non-SOEs and the small, statistically insignificant change for SOEs observed in Panel B. One possible explanation is that SOEs are more directly subject to government control and closer regulatory scrutiny, making them a more reliable channel for implementing policy objectives.

Together, the findings are consistent with the view that local governments strategically use SOEs to absorb regulatory pressure: by expanding SOEs' presence in less-polluting sectors within treated regions, and in polluting sectors within neighboring cities, local governments can mitigate the economic costs of environmental regulation while complying with policy mandates.

Regardless of local governments' formal authority over SOEs, purely political motives cannot fully explain the observed change in capital stock. A complementary economic mechanism operates through preferential access to capital goods: local governments can facilitate SOEs' financing and procurement, which lowers their effective cost of investment and aligns

[21] The contribution of SOEs is calculated as $x = 1 - w \cdot \frac{\beta_{\text{soe}}}{\beta}$, where w is the output share of SOEs (22.5 percent), β_{soe} is the coefficient for $KCAPC \times Post$ in Column 4, Panel A, Table 9, and β is the corresponding coefficient in Column 5, Panel B, Table 6.

firms' decisions with the goal to circumvent regulation. Indeed, SOEs were in an advantageous position during this period to capitalize on such fiscal and financial support (Firth et al., 2009). Empirical evidence supports this channel: Berkowitz et al. (2017) documents a rise in capital intensity among Chinese SOEs in the same era. Consistent with this pattern, Table B10 shows that SOEs in treated cities of less-polluting sectors experienced larger increases in capital stock than pollution-intensive sectors, whereas in neighboring, unregulated regions, the reverse holds. This sector-specific capital investment highlights the role of economic incentives, alongside political mandates, in driving the strategic expansion of SOEs and shaping the regional industrial structure.

6.3 Entry and Exit

Lastly, I study how KCAPC affects entry and exit in treated and neighboring cities, which offers more insight into how firm location decisions are affected. I show that entry and exit patterns reinforced sectoral change but did not drive it, consistent with the dynamics predicted by the PHH.

An important preliminary step in the analysis is to accurately identify firm entry and exit.

Identifying entering firms is particularly challenging due to the nature of the ASIF dataset, which only surveys non-state-owned enterprises with annual sales above 5 million yuan. To approximate firm entry as accurately as possible, I define an entering firm as one that appears for the first time in the sample, subject to two additional criteria based on its reported birth year. First, I exclude firms whose birth year precedes 1998, the first year of the sample. This removes older firms that might be mistakenly classified as new entrants due to the limited sample window. Second, I exclude firms whose birth year is before the policy treatment year (2002), but whose first appearance occurs after 2002. This ensures that all firms identified as entrants after 2002 are indeed newly established after the policy was implemented.

For exiting firms, I define exit as the last year a firm appears in the sample. However, I exclude firms whose last observation is in 2007, which is the final year of the dataset, as it is unclear whether those are true exits or simply a result of the dataset ending.

I examine whether the observed reallocation operates through changes at the extensive margin by estimating the effects of the policy on entry rate, exit rate, and net entry at the city–sector level (Table 10).

The results in Panel A show that in treated regions, polluting sectors experience a significantly higher exit rate and a lower net entry rate (Columns 1 and 3), consistent with some firm turnover away from polluting activities. However, the combined effects are small in magnitude and close to zero, suggesting that firm entry and exit account for only a limited share of the overall adjustment. In neighboring regions (Panel B), there are no statistically significant effects on either entry or exit.

Taken together, these findings indicate that the extensive margin is not the primary channel through which the policy affects industrial composition. Instead, the reallocation appears to occur mainly along the intensive margin — that is, through adjustments among incumbent firms, such as expansion of less-polluting producers or contraction within polluting sectors. This interpretation aligns with the evidence of shifting output and capital toward cleaner sectors and with the role of state-owned enterprises in facilitating adjustment.

7 Conclusion

How does the choice of spatial scale influence empirical support for the Pollution Haven Hypothesis, and through which mechanisms do any effects operate? To address these questions, I examine China's Key Cities Air Pollution Control (KCAPC) program — a regional policy that imposes stricter controls on pollution-intensive sectors — and evaluate its environmental and economic consequences. Specifically, I analyze aggregate outcomes (total emissions and pollution intensity) alongside sector-specific responses in output, capital, and employment.

Using a synthetic difference-in-differences approach to construct credible counterfactuals, I find that the KCAPC policy significantly reduces pollution intensity only among the most polluting (top-quintile) sectors. Building on this result, I classify sectors by pollution intensity and uncover evidence consistent with the Pollution Haven Hypothesis at the regional level: treated cities shift toward less-polluting sectors, while neighboring, non-regulated cities expand in pollution-intensive activities. Further analysis reveals that these patterns are driven by two key mechanisms: strategic reallocation by local governments through state-owned enterprises (SOEs), and firms switching their major production activities toward less pollution-intensive sectors.

These findings underscore the importance of spatial context in evaluating environmental regulations, with implications for both academic research and policy design. While such regulations may not fundamentally reshape economic structure at a national or global scale, they can induce substantial reallocation at more granular, regional levels. This highlights the need for environmental policy debates to account for spatial spillovers and interregional dynamics, as the effectiveness and consequences of regulation may vary significantly depending on geographic scope.

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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	1st	2nd	3rd	4th	5th
KCAPC × Post	0.028	-0.064	0.003	0.019	-0.119*
	(0.911)	(0.611)	(0.980)	(0.828)	(0.080)
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	860	1,150	1,430	1,940	2,110

Notes: p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the city level. Sectors are grouped and collapsed into five equally sized categories (quintiles) based on pollution intensity.

Table 4: Variable Definitions

Variable Name	**Definition**
KCAPC	A dummy that equals 1 for second round KCAPC cities
Nb	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
$\mathrm{SO2e_{tot}}$	Total sulfur oxide ($\mathrm{SO_2}$) 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)
TFP	Firm average Total Factor Productivity calculated using Olley and Pakes (1992)

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 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							
KCAPC × 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							
KCAPC × Post	0.087	0.109	0.441**	0.181***	0.142*	0.002	0.125
	(0.500)	(0.396)	(0.017)	(0.006)	(0.073)	(0.974)	(0.135)
Pol × Post	0.253**	0.254**	-0.024	-0.011	-0.300***	-0.242***	-0.311***
	(0.045)	(0.047)	(0.873)	(0.719)	(0.000)	(0.000)	(0.000)
KCAPC × Post × Pol	-0.297**	-0.288*	-0.554**	-0.024	-0.067	-0.071	-0.089
	(0.045)	(0.053)	(0.014)	(0.562)	(0.559)	(0.356)	(0.505)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.210	-0.179	-0.113	0.157	0.075	-0.069	0.036
City-Sector FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	2,089	2,089	2,563	2,640	2,376	2,640	2,376
R-squared	0.798	0.806	0.792	0.967	0.961	0.970	0.948

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

Table 7: 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							
Nb × 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							
Nb × 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 × 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)
Nb × Post × 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 Nb × Post and $\hat{\beta}_3$ represent Nb × Post × Pol. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors. Same for the following tables.

Table 8: Results for Firms Switching Products

VARIABLES	(1) Switch	(2) ln(Output)	(3) ln(Emp)	(4) ln(Cap)
KCAPC × Post	0.003**			
	(0.030)			
KCAPC × Post × 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)	(2)	(3)	(4)	(5)	(6)
	ln(Nfirms)	ln(Output)	ln(Nfirms)	ln(Output)	ln(Nfirms)	ln(Output)
Panel A. Treated Cities						
KCAPC × 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)
KCAPC × 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						
Nb × 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)
Nb × 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			
KCAPC × Post	-0.027**	-0.007	0.021
	(0.023)	(0.568)	(0.194)
Pol × Post	-0.013	-0.012	0.002
	(0.216)	(0.282)	(0.897)
KCAPC × Post × Pol	0.026**	-0.002	-0.028*
	(0.039)	(0.869)	(0.100)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.001	-0.009	-0.009
Observations	2,112	2,376	2,112
R^2	0.330	0.642	0.510
City-Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel B. Neighboring Cities			
Nb × Post	-0.017	-0.013	0.004
	(0.186)	(0.285)	(0.804)
Pol × Post	-0.014	-0.014	0.001
	(0.180)	(0.203)	(0.949)
Nb × Post × Pol	0.012	0.009	-0.002
	(0.339)	(0.469)	(0.893)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.005	-0.004	0.002
Observations	3,120	3,510	3,120
R^2	0.306	0.626	0.500
City-Sector FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

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

Figures

Figure 1: Map of KCAPC Cities

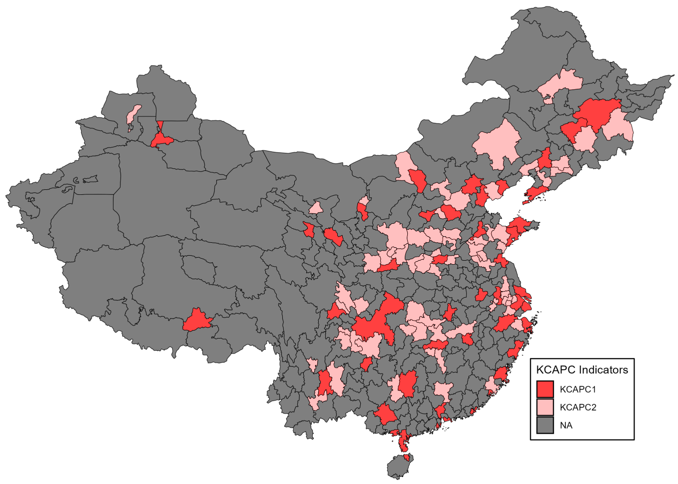
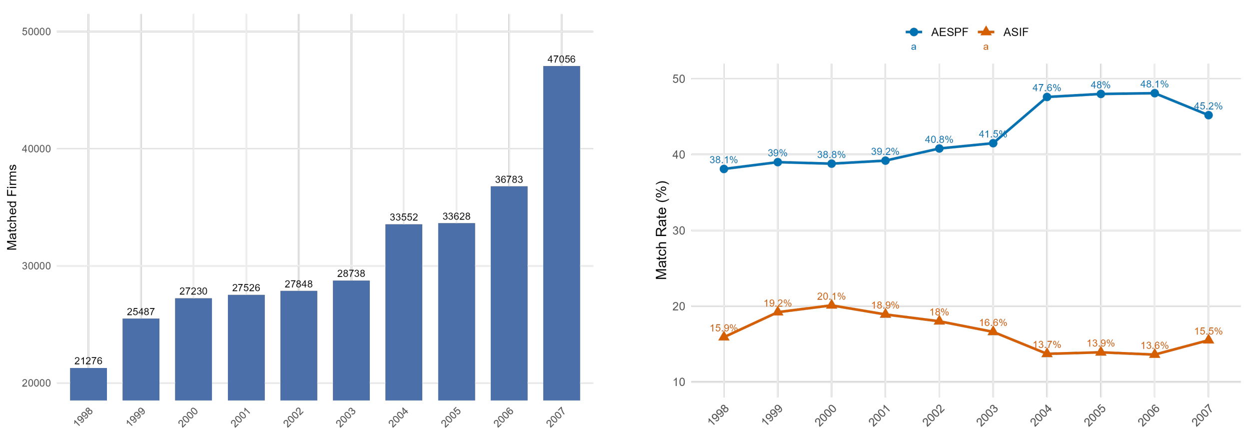


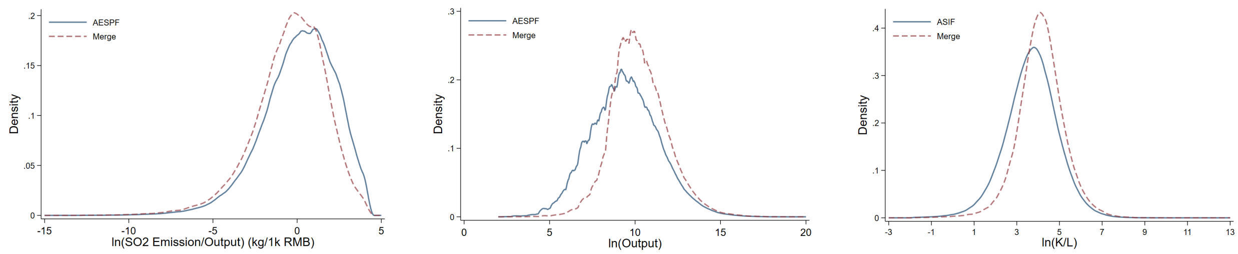
Figure 2: Merge results for ASIF and AESPF



(a) Matched Firms (bar chart) (b) Match Rates (ASIF vs AESPF)

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

Figure 3: Distribution of Key Stats Between Datasets



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

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

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

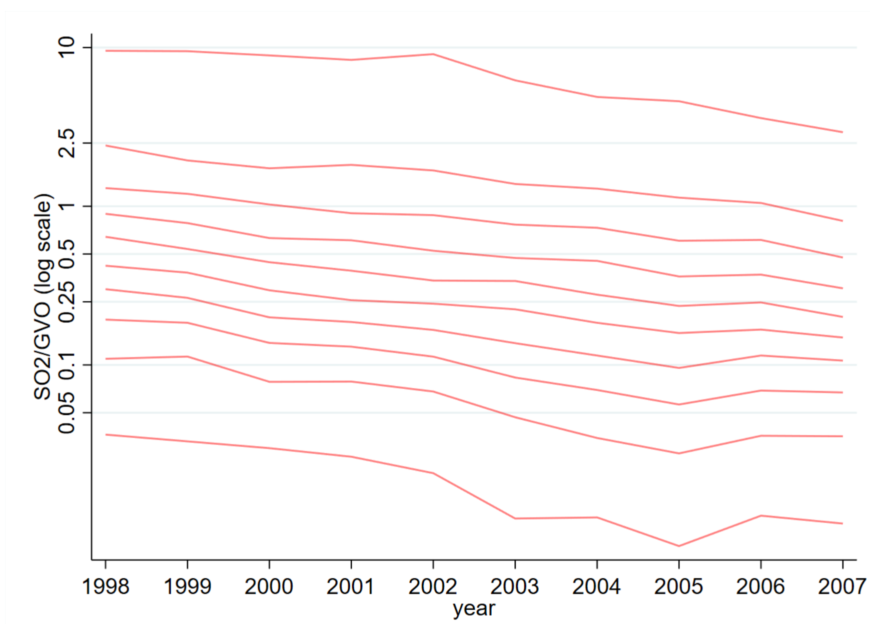
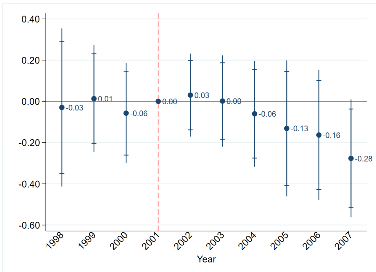
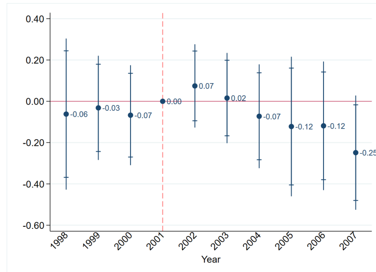


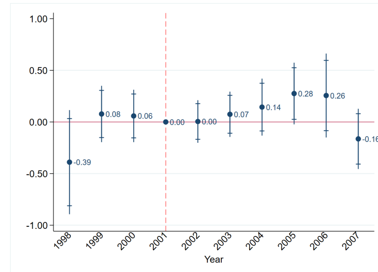
Figure 5: Pre-trend for Aggregate Effects in Treated Cities



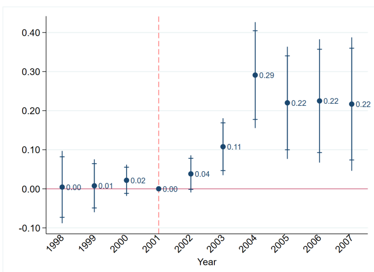
(a) SO_2 Emission Intensity



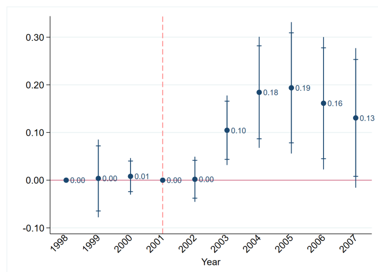
(b) SO_2 Generation Intensity



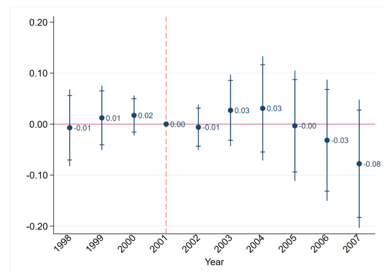
(c) Total SO_2 Emission



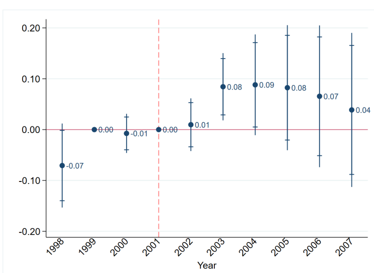
(d) Nfirms



(e) Output



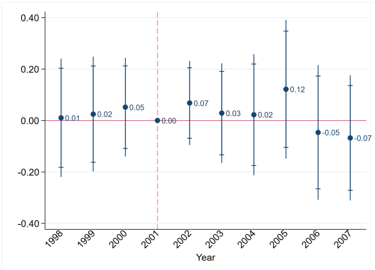
(f) Employment



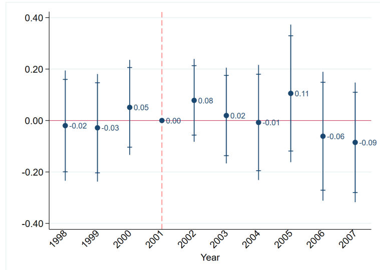
(g) Capital Stock

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

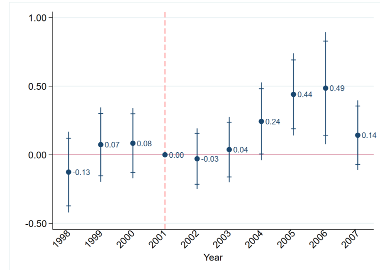
Figure 6: Pre-trend for Aggregate Effects in Neighbor Cities



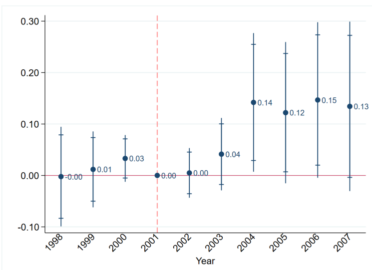
(a) SO_2 Emission Intensity



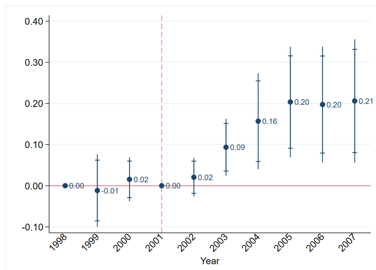
(b) SO_2 Generation Intensity



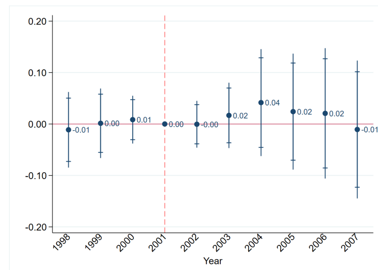
(c) Total SO_2 Emission



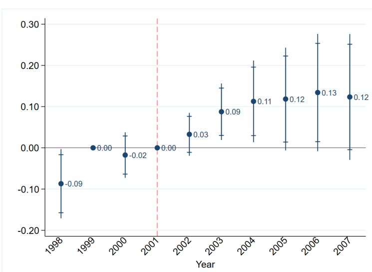
(d) Nfirms



(e) Output



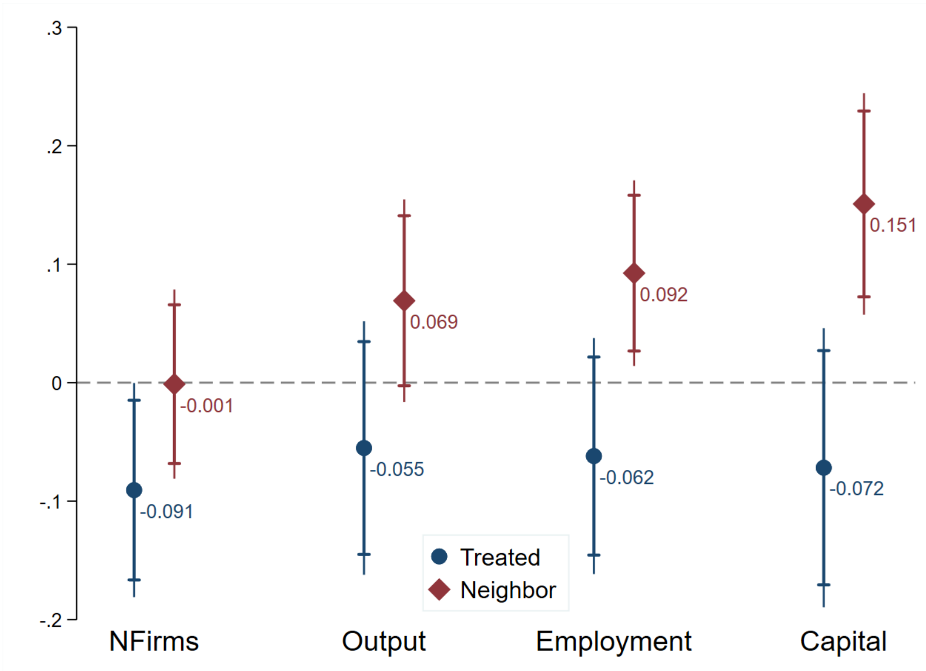
(f) Employment



(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: Change in zLQ after 2002 for Treated and Neigbor Cities



Note: This figure plots the coefficients as well as their respective confidence intervals (CIs) for the standardized location quotient index for polluting sectors of different economic outcomes.

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:

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

Where $W_{ct} = KCAPC_c \times Post_t$, 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
KCAPC	-0.019
	(0.247)
Nb	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
KCAPC × Post	0.029	0.090
	(0.878)	(0.545)
Pol × Post	-0.061	-0.060
	(0.683)	(0.682)
KCAPC × Post × Pol	-0.102	-0.172
	(0.626)	(0.343)
$\hat{\beta}_1 + \hat{\beta}_3$	-0.073	-0.082
Observations	2,257	3,323
R-squared	0.722	0.671
City-Sector FE	Yes	Yes
Year FE	Yes	Yes

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

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

	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)
KCAPC × 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)
KCAPC × 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 B4: Effects on Neighboring Cities: Controlling for City-Sector and Sector-Year FEs

	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)
Nb × 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)
Nb × 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 B5: Effects of KCAPC on Sectoral Shares

VARIABLES	SO2e	Nfirms	Output	Employment	Capital
Panel A. Treated Cities					
KCAPC × Post	-0.065**	-0.004	-0.017	-0.019	-0.017
	(0.038)	(0.651)	(0.463)	(0.241)	(0.490)
Observations	1,295	1,320	1,188	1,320	1,188
R-squared	0.528	0.902	0.836	0.877	0.811
Panel B. Neighboring Cities					
Nb × Post	0.013	0.009	0.021	0.013	0.045***
	(0.539)	(0.265)	(0.194)	(0.219)	(0.003)
Observations	1,907	1,950	1,755	1,950	1,755
R-squared	0.583	0.903	0.880	0.921	0.874

Notes: P-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Both panel control for both city and year fixed effects.

Table B6: Annual Percentage of Switching Firms by Region

	Firms (%)			Output (%)			SO_2 Emission (%)		
	Treated	Neighbor	Control	Treated	Neighbor	Control	Treated	Neighbor	Control
1998	3.5	2.8	2.6	8.7	5.3	5.1	20.3	8.9	11.6
1999	4.0	3.2	2.9	8.8	5.7	5.2	23.5	12.8	9.0
2000	4.5	3.6	3.3	9.0	6.1	5.3	22.8	11.3	12.1
2001	5.0	4.2	3.7	9.9	7.1	5.6	30.0	10.8	10.4
2002	5.3	4.4	3.8	9.8	7.5	5.6	28.5	11.6	12.0
2003	5.3	4.5	4.0	10.0	8.2	5.9	27.9	13.5	13.3
2004	3.8	3.4	3.1	9.8	8.0	5.2	20.0	12.9	12.8
2005	3.8	3.2	2.8	10.1	8.2	5.4	19.5	12.6	15.2
2006	3.2	2.6	2.3	9.3	7.2	4.6	20.3	12.4	14.4
2007	2.7	2.1	1.9	8.8	6.6	4.8	22.2	12.2	7.7

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: Annual Share of non-Privatized SOEs

	Firms (%)			Output (%)			SO_2 Emission (%)		
	Treated	Neighbor	Control	Treated	Neighbor	Control	Treated	Neighbor	Control
1998	95.3	95.7	95.1	95.9	92.7	91.6	96.5	97.2	94.4
1999	89.6	90.0	88.7	93.1	90.6	86.2	94.3	94.7	88.6
2000	82.6	84.3	82.1	90.0	86.3	82.4	92.2	91.1	79.6
2001	77.7	79.6	79.2	86.7	84.3	81.6	86.0	88.4	79.8
2002	73.6	74.7	74.4	86.6	80.3	78.4	89.5	86.4	83.6
2003	65.5	66.4	66.9	83.6	74.2	76.2	86.9	77.2	82.1
2004	60.2	59.9	58.7	79.4	65.8	60.6	82.5	57.5	72.3
2005	53.2	51.3	53.2	78.5	59.9	63.7	86.7	55.4	59.1
2006	56.8	52.8	55.8	82.9	67.2	73.4	87.9	64.5	65.9
2007	54.7	49.6	50.6	81.1	68.0	72.1	87.3	70.9	72.2

Notes: Each cell reports the share of SOEs that are not privatized in terms of the number of firms, total output, or SO_2 emissions for the given year and region. Values are expressed as percentages and rounded to one decimal place.

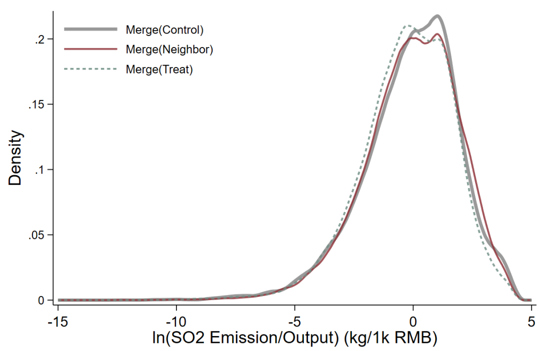
Table B10: Effect on Capital Stock by State-Ownership and Region

	Treated Cities		Neighbor Cities	
	(1) SOEs	(2) Non-Soes	(3) SOEs	(4) Non-Soes
KCAPC × Post	0.406***	0.054	-0.041	0.183**
	(0.000)	(0.485)	(0.648)	(0.032)
Pol × Post	-0.193*	0.062	-0.149*	0.085
	(0.066)	(0.463)	(0.090)	(0.319)
KCAPC × Post × 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

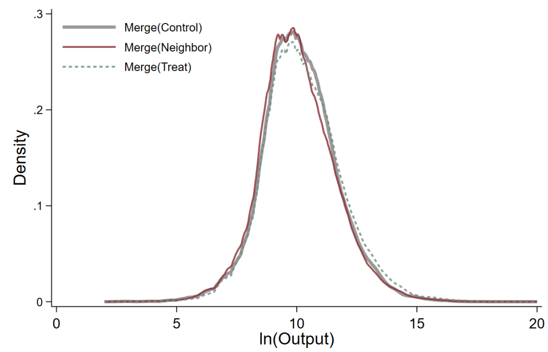
Notes: P-values in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the city level. $\hat{\beta}_1 + \hat{\beta}_3$ reports the combined effect on polluting sectors.

C Additional Figures

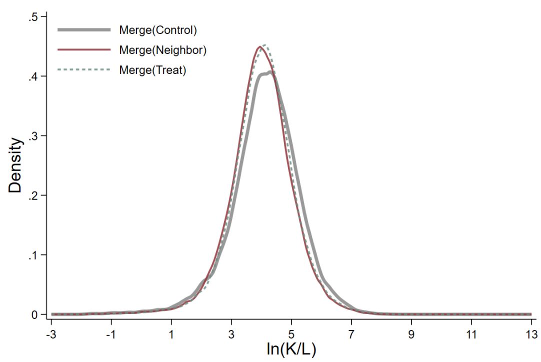
Figure C1: Distribution of Key Stats by Treatment Groups



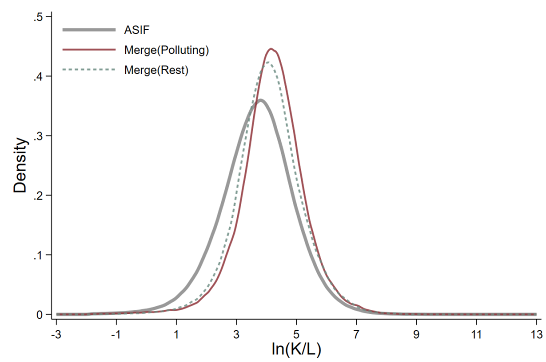
(a) Emission Intensity (by Region)



(b) Output (by Region)



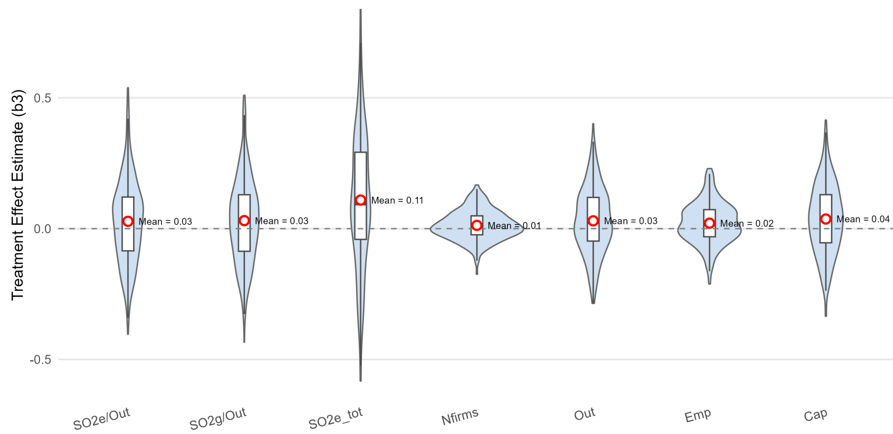
(c) K/L (by Region)



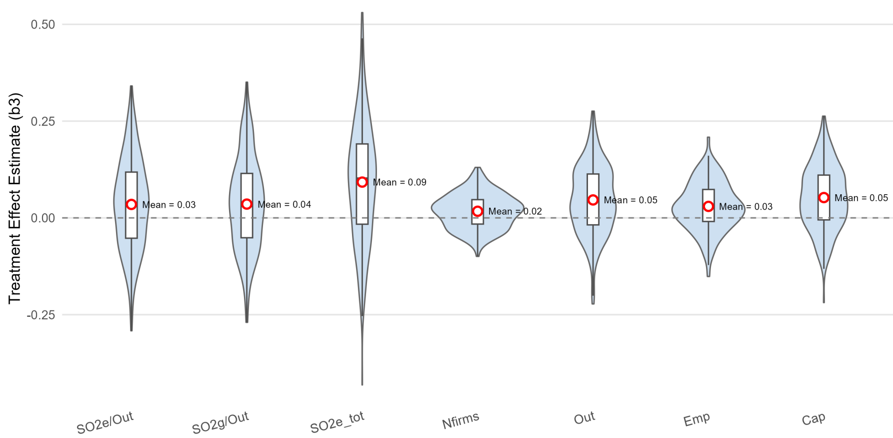
(d) K/L (by Sector)

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



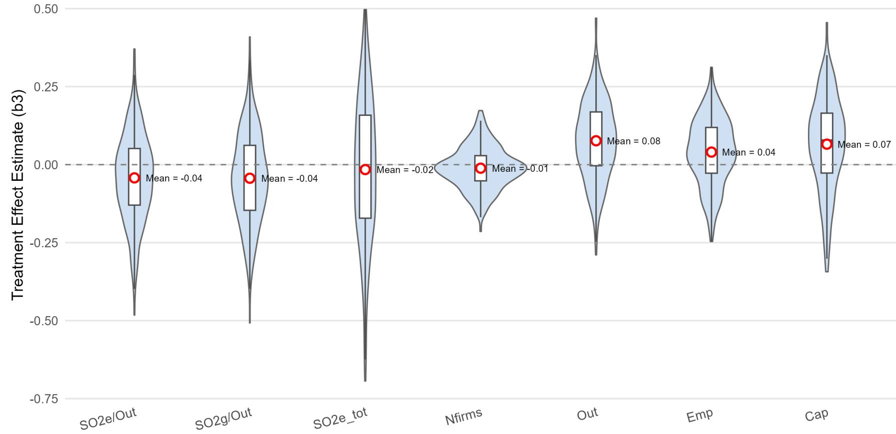
(a) Treated Cities



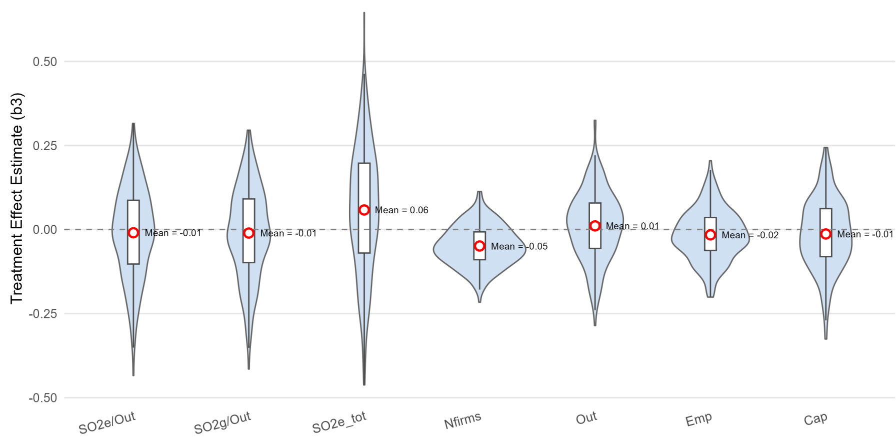
(b) Neighboring Cities

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 C3: Distribution of $\hat{\beta}_3$ for Random Polluting Sectors



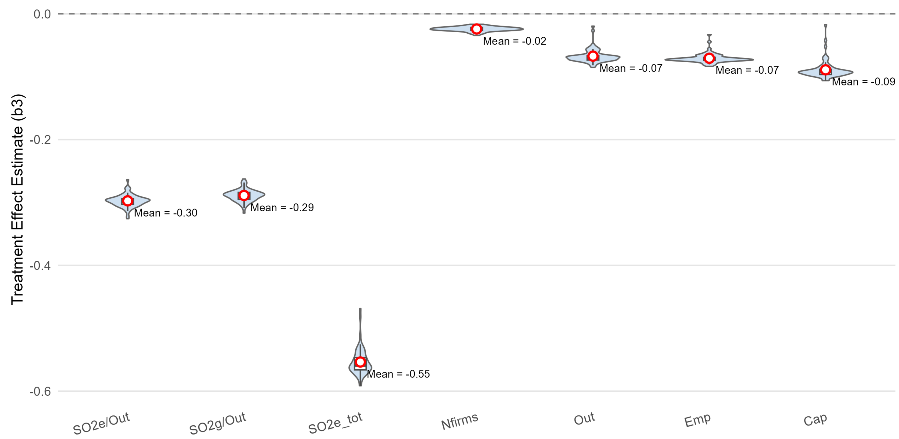
(a) Treated Cities



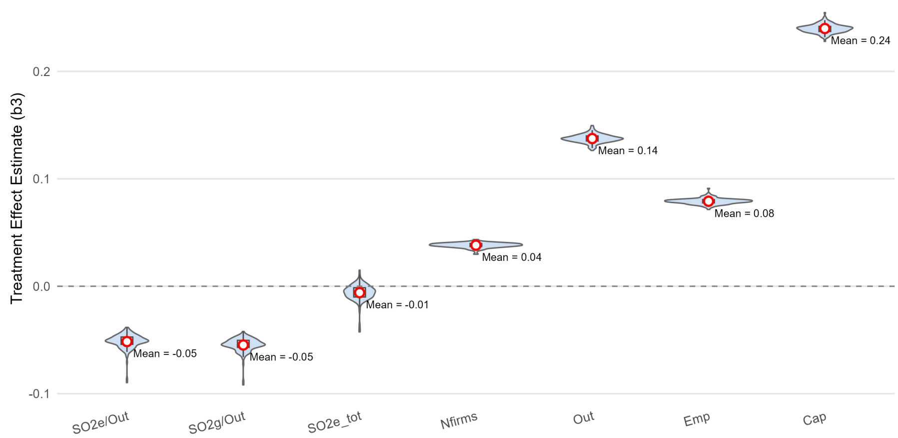
(b) Neighboring Cities

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 C4: Distribution of $\hat{\beta}_3$ for Leave-One-Out Cities



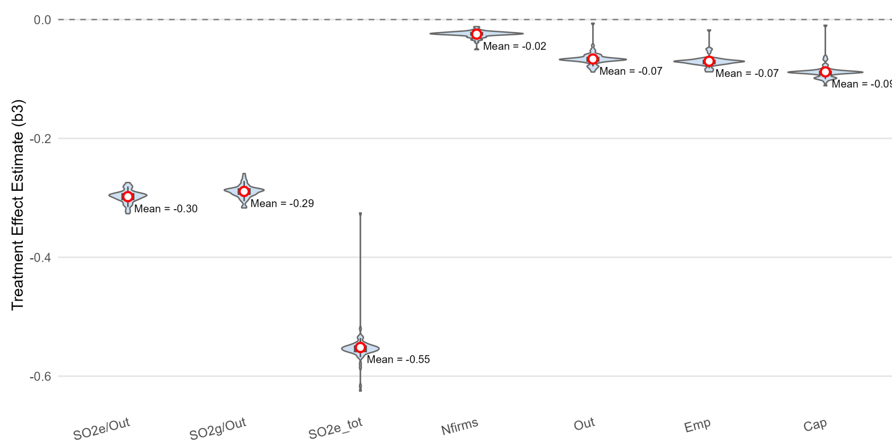
(a) Treated Cities



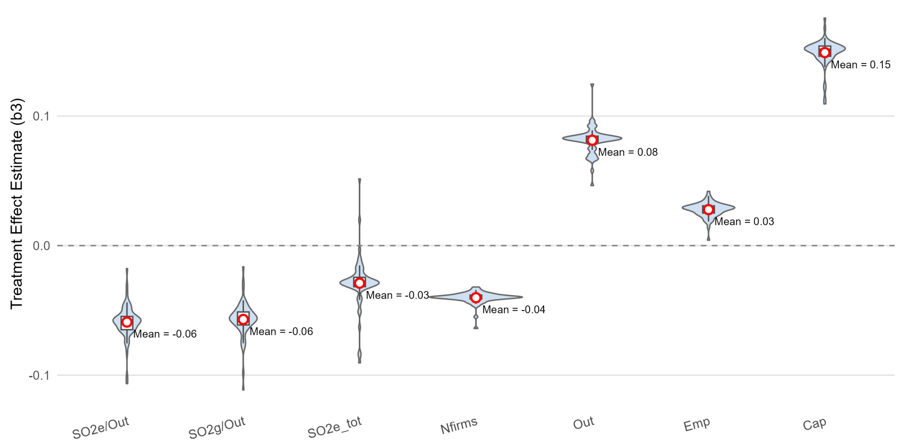
(b) Neighboring Cities

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



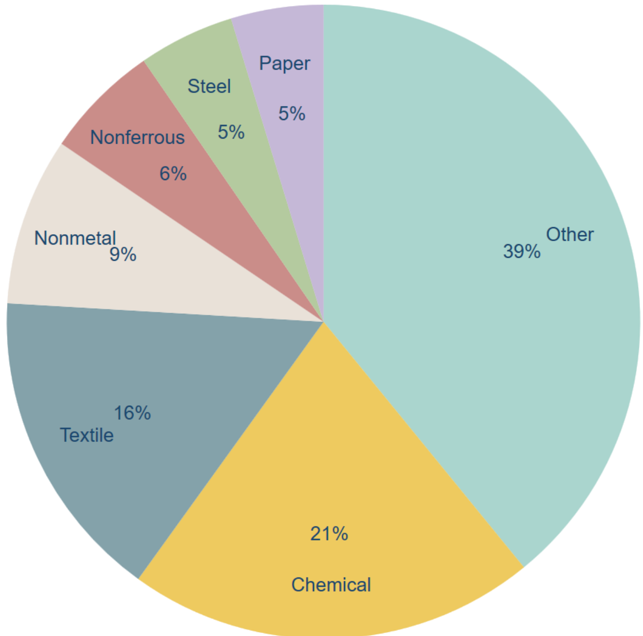
(a) Treated Cities



(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 C6: 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.