The Geographical Leakage of Environmental Regulation: Evidence from the Clean Air Act

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Abstract

How large is geographic leakage resulting from place-based environmental policy? We study this question in the context of the landmark U.S. Clean Air Act Amendments. We make three contributions. First, using modern event-study techniques and confidential U.S. Census data, we revisit seminal results characterizing the effects of this regulation on directly regulated plants and industries, documenting large and persistent declines in employment and sales driven in part by plant exit. Second, we extend prior research by quantifying leakage to unregulated regions and identifying multi-unit firm networks as a central conduit for this reallocation. We show that firms expand activity at unregulated plants and that counties more exposed to nearby regulation experience positive employment spillovers. Third, we integrate these findings into an industry spatial equilibrium model with intra-national trade and multi-plant production. The model implies that the regulation raised prices by roughly 2% while reducing pollution-related mortality by 1.7%, saving approximately 10,500 lives annually. It further shows that a substantial share of the observed relative employment decline reflects leakage to unregulated domains, underscoring the importance of multi-unit firm networks for evaluating the aggregate costs and environmental benefits of environmental policy.

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JEL Codes: Q52, R12, L25

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1 Introduction

A central question in the study of environmental regulation is the extent to which regulated activity is displaced to unregulated domains. When policies apply unevenly—across plants, firms, sectors, or locations—firms may respond by reallocating production. Ignoring such leakage can bias estimates of treatment effects and misstate both the economic costs and environmental benefits of regulation.

In this paper, we study these issues in the context of a landmark environmental legislation: the Clean Air Act Amendments (CAAA). The policy imposed stricter regulation on manufacturing plants located in counties that exceeded federal pollution standards, creating sharp differences in regulatory stringency across otherwise integrated markets. This setting provides a natural laboratory to quantify both the direct effects of regulation and the extent of leakage to unregulated domains.

Four main challenges have limited our understanding of the direct and indirect effects of environmental regulation. First, leakage complicates the estimation of treatment effects, since activity in unregulated domains may respond endogenously to policy. Second, command-and-control regulations often affect investment and plant configuration gradually, making short-run analyses ill-suited to capture long-run extensive-margin adjustments such as entry, exit, and within-firm reallocation. Third, because a large share of industrial output is produced by multi-unit firms, measuring leakage requires tracking production across ownership networks. Finally, regulatory differences are often correlated with underlying economic conditions, raising concerns about omitted variable bias and policy endogeneity. Such endogeneity may swamp reallocation effects, potentially leading researchers to conclude that environmental regulation is not an important driver of industry location decisions (Copeland, Shapiro, and Taylor, 2022).

We overcome these challenges by combining new empirical evidence with a spatial equilibrium model that features intra-national trade and multi-unit production. We begin by using confidential plant- and firm-level data from the U.S. Census Bureau to study the effects of the Clean Air Act over a twenty-year horizon. Our event-study approach captures long-run adjustments, including plant exit and reallocation within firms. By linking regulated plants

to their unregulated sister plants, we directly measure within-firm leakage—an important margin given that multi-unit firms accounted for roughly 80% of output in regulated industries during this period. In addition, we provide new county-level estimates that document geographic spillovers across neighboring regions.

Using event-study specifications, we find that, relative to unregulated plants, those located in nonattainment areas experience substantial and persistent declines in economic activity. Over a twenty-year horizon, employment falls by 26% and sales by 30%. A significant portion of these changes reflects extensive-margin adjustments, particularly plant exit among multi-unit firms. We further show that firms exposed to regulation expand activity at their unregulated plants, providing direct evidence of within-firm leakage.

We complement our evidence of within-firm reallocation with new estimates of geographic leakage across counties using publicly available County Business Patterns data (Eckert et al., 2020). To measure indirect exposure, we construct a distance-weighted index of nearby regulated employment following the spatial exposure approach in Adao, Arkolakis, and Esposito (2025). County-level estimates reveal that employment in regulated areas declines by 25%, while counties more exposed to nearby regulation experience positive spillovers.

While these empirical estimates capture relative differences between regulated and unregulated areas, they do not separately identify the direct effect of regulation on treated locations from the equilibrium responses of untreated ones. To quantify these mechanisms and assess aggregate effects, we build a spatial equilibrium model with intra-national trade and multi-unit production. Calibrated to match the reduced-form evidence, the model implies that rationalizing the observed employment decline requires a 3.5% reduction in local productivity in regulated areas, comparable to that estimated in Greenstone, List, and Syverson (2012). As evidence that the model captures the economic forces at play, we show that standard values of the within-firm elasticity of substitution (Tintelnot, 2017; Head and Mayer, 2019) perform remarkably well at reproducing our (untargeted) spillover estimates.

Importantly, the model shows that difference-in-differences estimates combine two forces: contraction in regulated regions and expansion in unregulated ones. In our baseline calibration, roughly 60% of the relative employment decline reflects reduced activity in regulated areas, while about 40% reflects leakage to unregulated locations. Incorporating multi-unit

firms is essential to reproducing both within-firm and cross-location spillovers. A model without multi-unit production substantially understates spatial reallocation and fails to match the observed spillovers.

The model further allows us to quantify aggregate economic and environmental consequences. In equilibrium, the regulation raises prices in regulated industries by about 2%, implying a modest consumption cost that varies across space. At the same time, combining model-implied production changes with a pollution transport framework, we estimate a 1.7% decline in pollution-related mortality, corresponding to roughly 10,500 lives saved annually. Integrating these economic and environmental effects, we recover a break-even value of a statistical life of approximately $70,000 (in 1970 USD), substantially below commonly used benchmark values. Importantly, these effects are highly heterogeneous across regions.

Taken together, our findings show that when regulation applies unevenly across space, economic activity adjusts through firm networks, trade linkages, and entry and exit decisions. Ignoring these equilibrium responses can distort the interpretation of reduced-form estimates and misstate both the aggregate costs and environmental benefits of policy. More broadly, our results highlight the importance of incorporating multi-unit production networks into the evaluation of environmental regulation, as these networks shape not only the magnitude of spatial reallocation but also the aggregate and regional incidence of regulatory impacts.

The rest of the paper is organized as follows. Section 2 places our results in the context of the literature. Section 3 provides institutional background on the Clean Air Act Amendments. Section 4 develops a simple, two-location model with intra-national trade and multi-unit firm production that motivates the challenges of interpreting difference-in-differences estimates in spatial equilibrium. Section 5 describes our data and empirical results. Section 6 generalizes and implements our quantitative model. Section 7 uses the model to evaluate the direct, indirect, and aggregate effects of the Clean Air Act. Section 8 concludes.

2 Related Literature

To set the stage, we revisit seminal papers in the literature on the economic effects of the 1970 Clean Air Act such as Greenstone (2002) and Becker and Henderson (2000).[1] Consistent with the findings in this literature, we estimate that violations of the pollution standard increase exit rates, particularly among very large establishments, and trigger declines in sales, employment and energy use. We make two contributions to this literature. First, we provide new evidence on the long-run effects of the policy. Clean Air Act (CAA) regulations may not immediately require incumbents to downsize, either because of grandfathering or modest cost of required control equipment. Over time, some of the provisions of the CAA become more binding and put regulated plants at a long-run disadvantage relative to unregulated plants. One such provision is the New Source Review that severely limits plants in their ability to carry out major expansions. Our event study methodology allows us to capture these long-run responses, and supports the hypothesis that the negative effects of regulation accumulate over time.[2] Taken at face value, the relative employment declines in polluting industries imply a job loss of more than 200 thousand, around four times larger than implied by Greenstone (2002) estimates for particulate matter regulation.[3] Second, we empirically test for leakage within firms and across counties triggered by the policy.

Our findings of within firm leakage complement recent work that studies these leakage in response to environmental policy (Cui et al., 2023; Gibson, 2019; Hanna, 2010), weather shocks (Castro-Vincenzi, 2023; Acharya, Bhardwaj, and Tomunen, 2023) and local productivity improvements (Giroud et al., 2021). An important take-away from our results is that this process of reallocation may take a long time to unfold. Thus, we caution against using short panels if the goal is to estimate the full extent of within firm reallocation. Relative to these papers, we also present evidence for gravity-based leakage to nearby unregulated counties. Spatial leakage within the US may be an important consideration for designing and evaluating environmental policies that differ across states (Fowlie, 2009).

[1] Similar to these studies, our paper only focuses on the manufacturing sector. Clay et al. (2021) study the effects 1970s nonattainment on electricity producers.

[2] Walker (2013) analyzes important long-run labour market outcomes among workers employed by regulated plants.

[3] These differences arise because Greenstone's difference in difference estimates also reflect substantially smaller short-run effects, as well as his assumption that counties are no longer regulated.

Accounting for leakage is central for estimating the aggregate effects of the policy. A large literature uses quantitative general equilibrium models to assess positive and normative aspects of environmental policy (Golosov et al., 2014; Hafstead and Williams, 2018; Shapiro and Walker, 2018; Campolmi et al., 2024). Papers in this literature typically study environmental policy at the national level, while we evaluate the distortions that arise in spatial equilibrium, similar to the study of state tax differences by Fajgelbaum et al. (2019). We explicitly discipline our model with credible reduced form estimates of the micro effects of environmental policy. Closely related to our quantitative analysis, Hollingsworth et al. (2022) also study the effects of the Clean Air Act in spatial equilibrium. Their paper highlights the importance of pollution transport for estimating the aggregate benefits of reduced pollution in nonattainment counties.[4] Relative to their work, we provide a detailed empirical assessment of economic leakage and interpret the empirical results within a spatial equilibrium model of multi-unit firm production. Our paper is also related to empirical work on the pollution haven hypothesis as surveyed in Copeland, Shapiro, and Taylor (2022). While the evidence in that literature is mixed, our study of intra-national relocation overcomes endogeneity issues that arise in cross-country studies. Since production is likely more mobile within than across countries, our estimates may provide a credible upper bound on pollution haven effects.

3 Institutional Setting

In this section, we describe the institutional features of the environmental regulation that serves as the foundation for our identification strategy and modeling framework.

3.1 Clean Air Act

The Clean Air Act was the first federal legislation regulating emissions of air pollutants in the United States. While it has undergone changes since its passage, the framework that was put in place by Congress in the 1970's remains intact today.[5] Following the Earth Day

[4] Hollingsworth et al. (2022) emphasize that unregulated counties can benefit from regulation through reduced pollution transport. We empirically estimate no pollution leakage to unregulated counties, consistent with economic reallocation offsetting the effects of reduced transport.

[5] The original Clean Air Act passed in 1963, but contained only broad, non-specific goals and no enforcement mechanisms. As a result, between 1963 and 1970, the act was viewed as toothless and "a complete

Demonstrations in April of 1970, Congress moved quickly to pass federal, enforceable regulations of air emissions. The 1970 Clean Air Act Amendments established the Environmental Protection Agency (EPA) and granted them considerable authority to regulate emissions across stationary and non-stationary sources. The backbone of the 1970 CAAA, was the creation of the National Ambient Air Quality Standards (NAAQS). The law gave the EPA authority to set air quality standards for pollutants considered harmful to public health and the environment. The NAAQS set pollution thresholds for key "criteria" air pollutants and regions of the country with pollution levels above these thresholds were designated as "nonattainment." Regions of the country whose pollution levels were below the threshold would be designated as in attainment. The 1970 CAAA required States to design and enforce State Implementation Plans (SIPs) by 1972 that would reduce emissions in nonattainment regions and bring these regions' pollution levels into compliance with the new federally imposed air quality standards. In practice, most states calculated the total estimated emissions from all stationary sources within each nonattainment area and then divided this figure by an estimate of the maximum emissions level that would allow to achieve attainment status. Plants were then mandated to cut emissions in accordance with this ratio (Roberts and Farrell, 1978).

While states had some leeway to regulate emitters, the EPA and the 1977 CAAA formalized a set of rules which required polluting establishments in nonattainment regions to comply with more stringent regulations than those in attainment regions. In particular, in order for a plant to receive an operating permit in a nonattainment region, it had to achieve the Lowest Available Emissions Rate (LAER). This provision of the CAAA required them to install capital that ensured they would achieve the emissions rate of the cleanest plant in the industry. Importantly, this standard had to be implemented "irrespective of cost", requiring firms to make expensive upgrades to their facilities. Additionally, as part of the Nonattainment New Source Review, new and modified sources in nonattainment regions were required to obtain offsets from other local emitters before any expansion or modification would be allowed (Shapiro and Walker, 2023). Finally, being located in a nonattainment region meant that plants were now subject to scrutiny from regulators and the public. Facilities wishing

failure" (Melnick, 1983).

to modify or grow were required to undergo an extended period of public and regulatory input. Polluting establishments in attainment regions and particularly those without emissions monitors, received far less scrutiny from regulators.

More lax rules were put in place for plants in attainment counties. "Major Sources" in attainment regions were subject to the less stringent Prevention of Significant Deterioration (PSD) requirements which took costs and economic growth into consideration and did not require public input for new and modified sources. However, the definition of a major source varied by attainment status. Generally, plants in nonattainment regions were defined as major source emitters if they produced more than 100 tons per year of a pollutant. Plants in attainment counties could pollute up to 250 tons per year before being classified as a major source.

Together, the introduction of the 1970, 1977 Clean Air Act Amendments, and the establishment of nonattainment standards, marked a significant turning point for industrial polluters, imposing stringent regulatory measures that were unprecedented at the time.

3.2 Details of Treatment Designation

The geographic variation we exploit in our analysis is derived from the differential change in regulatory stringency between plants in attainment and nonattainment regions following the passage of the 1970 CAAA. Upon its passage, the EPA collected air quality data from pollution monitors around the country to determine which regions would be designated as nonattainment for the criteria air pollutants. By the beginning of 1972, the EPA had developed a designation. The EPA did not publish records of county nonattainment designation until 1978. As a result, researchers use monitor data from the early 1970's together with the published pollution thresholds to impute which counties were originally placed into nonattainment (see Sanders and Stoecker (2015) and Isen, Rossin-Slater, and Walker (2017) among others). Researchers have differed in the details of imputation, but recent work has focused on attainment status of Total Suspend Particulates, for which the monitor network is most complete in the early 1970's when attainment status was first being determined (Cropper et al., 2023; Isen, Rossin-Slater, and Walker, 2017; Sanders and Stoecker, 2015).[6]

[6]In 1972, TSP monitors covered 1,059 counties, relative to 508 for SO2, 156 for O3 and 137 for CO.

As a result, our main analysis defines a county as treated if it is designated as nonattainment for at least TSP. When using available data for monitors of other pollutants we find that, unsurprisingly, nonattainment status is highly correlated across pollutants. We identify only 25 counties which fall above the threshold for a non-TSP pollutant and would be defined as in attainment for TSP.[7] From these readings, 274 counties whose 1971/1972 monitor data exceeded the CAAA's Total Suspended Particulates threshold are defined as treated.[8]

We take these regulatory designations as fixed for the period 1972 to 1987. An alternative considered in Greenstone (2002) is to assume plants are no longer regulated once the county achieves the primary standard. One advantage of taking regulatory designations as fixed is that it allows us to estimate the dynamic effects of nonattainment. Long-run effects may be important because some aspects of the regulation such as the New Source Review can affect firms even if they are no longer directly targeted by regulators. If firms stop investing while regulated, the effect on output may remain visible even if the county has fallen back into attainment. An additional consideration is that regulatory differences may in fact be permanent. Even if pollution readings fall below the initial threshold, a county can still be in violation for NAAQS standards which were lowered in subsequent years. The thresholds used to determine attainment status have been revised and lowered almost every five years. Plants in initially more polluted nonattainment areas may expect future tightening of the NAAQS to fall on them and thus not dramatically change their behavior.

Following Greenstone (2002) and Greenstone, List, and Syverson (2012), our baseline results analyze industries that are deemed as heavy polluters. We provide additional details of the selected industries in Section 5.1.

[7] To create a clean control group we drop plants in these 25 counties from our sample. Given Census disclosure rules we currently do not release results for other treatment definitions but we are able to perform a number of robustness checks with other treatment definitions using publicly available County Business Patterns data.

[8] A second reason to focus on TSP, apart from the sparse monitor data of other pollutants, is that the CAA officially targeted larger Air Quality Control Regions (AQCR) in the early 1970s (Murphy, 2017; Cropper et al., 2023). For TSP, it is plausible that regulators focused on the most polluted counties within AQCRs since TSP pollution remains highly concentrated around its source (Auffhammer, Bento, and Lowe, 2009). Appendix C provides additional details on treatment designation and robustness checks using AQCR definitions.

4 Theoretical Motivation

To build intuition about the economic effects of partial regulation in the presence of multi-plant production, we begin with a simple two-region model. This simple case shows that, in spatial equilibrium, comparisons between plant outcomes across attainment and nonattainment regions do not isolate the direct effect of regulation. A productivity decline in the nonattainment region improves the relative competitiveness of plants in the attainment region, and equilibrium production and employment in each region depend jointly on the price indices in both markets. More interestingly, the model predicts that unregulated plants with a regulated sister plant could further experience higher employment and sales as activity reallocates within the firm. This intra-firm leakage effect arises whenever the elasticity of substitution across plants within firms is greater than the elasticity of substitution across firms. Proofs of these results are in Appendix D.

Set-up. There are two ex-ante symmetric locations. Each location j has a unit mass of firm j with firm productivity $\phi \sim G_j$. Firms produce differentiated varieties using labor. We focus on the product market equilibrium and normalize the wage $w_j = 1$ in both locations. A firm operating a single plant may ship to the other location, incurring a constant iceberg trade cost $\tau > 1$. Alternatively, firms may establish a second plant in the other location by paying a fixed cost f.

The key benefit of operating a multi-plant firm is a lower unit cost. For a single-plant firm ϕ located in j, the marginal cost of serving market j is

$$c_j^{SU}(\phi) = \frac{\Gamma_\theta}{\phi}\frac{1}{T_j}$$

where $\Gamma_\theta = \Gamma\left(\frac{\theta+1}{\theta}\right)$. In contrast, for a multi-plant firm, marginal cost of serving market j is

$$c_j^{MU}(\phi) = \frac{\Gamma_\theta}{\phi}\left(\left(\frac{1}{T_j}\right)^{-\theta} + \left(\frac{\tau}{T_{j'}}\right)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

In a symmetric baseline equilibrium with $\frac{1}{T_j} = \frac{1}{T_{j'}}$ we otain $\frac{c_j^{SU}(\phi)}{c_j^{MU}(\phi)} = \frac{1}{(1+\tau^{-\theta})^{-\frac{1}{\theta}}} > 1$. The MU firm achieves lower marginal cost by exploiting comparative advantage within the firm.[9]

[9]This cost function can either be taken as a model primitive or micro-founded following Tintelnot (2017): sales consist of a unit mass of shipments. Each plant draws shipment-level cost from a Fréchet distribution with region-specific location parameter T_j and common shape parameter θ. The firm assigns each shipment to the plant with the lowest cost draw. A detailed derivation is provided in Section 6.1.

Combined with the presence of fixed costs MU production, the model produces intuitive sorting. Let $\bar{\phi}_j$ denote the productivity of a location-j originated firm indifferent between single-unit production and multi-unit production. Under CES-monopolistic competition, this cutoff satisfies $\pi(\bar{\phi}_j)^{MU} = f + \pi(\bar{\phi}_j)^{SU}$, where $\pi(\cdot)$ is the total profit of the firm.

Effects of Environmental Regulation. We model nonattainment designation as a negative, location-specific productivity shock $d\ln T_j < 0$ to an ex-ante symmetric industry equilibrium.[10]Productivity $T_{j'}$ in the attainment region j' is unaffected. The following results characterize the effects of this shock to a first-order approximation.

Proposition 1. *The impact of regulation on revenue r and labor demand l of a single and multi-unit plant active in j is*

$$d\log r_j^{SU} = d\log l_j^{SU} = (\eta-1)\left(\omega^{SU} d\log P_j + (1-\omega^{SU}) d\log P_{j'}\right) + (\eta-1) d\log T_j$$

$$\begin{aligned} d\log r_j^{MU} = d\log l_j^{MU} &= (\eta-1)\left(\omega^{MU} d\log P_j + (1-\omega^{MU}) d\log P_{j'}\right) \\ &+ \underbrace{[\theta-(\eta-1)]}_{\textit{Within Firm Substitution}} \times [2\omega^{MU}(1-\omega^{MU})] d\ln T_j \end{aligned}$$

where $\omega^{SU} = \frac{1}{1+\tau^{1-\eta}}$ and $\omega^{MU} = \frac{1}{1+\tau^{-\theta}}$ denote the home-market revenue shares for single-unit and multi-unit plants, respectively.

This result highlights two channels through which environmental regulation affects plant-level outcomes. Holding destination prices fixed, a negative productivity shock in the nonattainment region directly reduces plant sales and employment.[11] For single-unit plants, this direct effect operates solely through the cross-firm elasticity of substitution η. For multi-unit plants, it reflects a combination of the across-firm elasticity η and the within-firm substitution elasticity θ, capturing within-firm production reallocation. At the same time, the productivity decline induces endogenous adjustments in destination price indices P_j and $P_{j'}$, transmitting the shock across locations via general-equilibrium demand reallocation. The exposure weights involving the trade cost τ correspond to the shares of plant revenue generated in the local and away markets.

[10]This equilibrium is defined by a pair of ideal price indices P_j and $P_{j'}$ that are consistent with optimal location and production choices of firms in j and j'.

[11]With labor as the sole input under CES monopolistic competition, sales and employment move proportionally up to a constant factor.

A direct implication of within-firm reallocation and equilibrium price adjustment is that regulation in location j also affects the revenue and labor demand of plants in the *unregulated* region j':

$$d\log r_{j'}^{SU} = d\log l_{j'}^{SU} = (\eta-1)\left((1-\omega^{SU})d\log P_j + \omega^{SU} d\log P_{j'}\right).$$

$$\begin{aligned} d\log r_{j'}^{MU} = d\log l_{j'}^{MU} &= (\eta-1)\left((1-\omega^{MU})d\log P_j + \omega^{MU} d\log P_{j'}\right) \\ &\quad - [\theta-(\eta-1)] \times [2\omega^{MU}(1-\omega^{MU})]\, d\ln T_j. \end{aligned}$$

For multi-unit plants, there is an additional reallocation effect: when $\theta > \eta - 1$, regulation in region j induces an increase in production at plants located in j'. Multi-unit firms substitute toward their unregulated plants to serve demand previously supplied by the regulated plant in j. This reallocation channel is strongest when trade costs τ were small. Regulation affects not only the intensive margin of production allocation but also the extensive margin of operating an additional plant in the foreign location. Our next result characterizes this extensive-margin response.

Proposition 2. *The effects of regulation on whether to operate in additional location are opposite in sign for nonattainment vs attainment locations:*

$$d\ln\bar{\phi}_j < 0 \quad \textit{and} \quad d\ln\bar{\phi}_{j'} > 0.$$

After the regulation, firms head-quartered in j are more likely to open a second plant in location j' if $\theta > \eta - 1$, i.e., the productivity threshold defining MU status decreases: $d\ln\bar{\phi}_j < 0$. The restriction $\theta > \eta - 1$ guarantees that the profits of single-unit firms are more negatively affected by the productivity decline than those of multi-unit firms. At the same time, having an additional plant in the regulated location j becomes less attractive for firms headquartered in j', where the multi-unit threshold increases: $d\ln\bar{\phi}_{j'} > 0$. Given the assumption of symmetry across locations, these results also imply that the overall number of active firms remains constant. Nonetheless, as the following result shows, the effects of the regulation on location choices amplifies the overall effect of the regulation on the price index in the regulated area P_j.

Proposition 3. *The effect of nonattainment on the price index is given by*

$$d \ln P_j = -\Lambda \times d \ln T_j \quad \textit{and} \quad d \ln P_{j'} = -(1-\Lambda) d \ln T_j,$$

where $\Lambda > (1 - S_{Trade}) > \frac{1}{2}$ *is a function of model parameters.*

In a setting without entry and location choices, the first-order effect of a negative productivity shock on P_j is given by share of consumption that was initially produced in j, which we denote by $1 - S_{Trade}$. Entry and exit decisions amplify this effect because the number of firms producing in j falls. The offsetting entry in j' is less valuable for consumers in j who are separated from these firms by trade frictions. Prices in location j' also increase whenever $\Lambda < 1$. This holds when the market share of marginal firms is sufficiently small or the trade cost is large enough so that the price index in location j' is not too elastic with respect to the behavior of these firms.

A corollary of the proposition above is that, when $\Lambda < 1$, a difference-in-difference comparison overstates the effects of regulation on local labor demand:

$$|d \ln L_j| < |d \ln L_j - d \ln L_{j'}|.$$

The response of local labor demand $d \ln L_j$ reflects the direct effect of the negative productivity shock on surviving firms, partially offset by the increase in the price index in j. A similar equilibrium adjustment leads to relocation of plants to the unregulated location j'. Together, these effects imply an increase in labor demand $d \ln L_{j'} > 0$. Thus, comparing a regulated area to an unregulated one only identifies the regulation's relative effect on labor demand. However, it overstates employment losses in the regulated area because the relative price increase is smaller than the absolute price increase in the nonattainment area. Additionally, this difference is amplified by the within-firm relocation too.

With knowledge of model parameters, such as Λ and the price elasticity of product demand, it is possible to use this simple model to decompose differences-in-differences estimates into the effects on attainment and nonattainment areas (see Appendix D). While this model delivers useful insights, the mapping between model parameters and reduced-form effects depends on an unrealistic assumption of symmetry, misses important differences in the economic geography of the US, and does not account for how the policy targeted different

locations. We will further address these important details in our quantitative analysis of section 6.1.

5 Empirical Results

5.1 Sources of US Manufacturing Data

This section describes the main data sources we use in our empirical analyses of the 1970's CAAA on plant-, firm- and county-level outcomes.

Plant-level data. The primary dataset we rely on is the Census of Manufactures (CM). The CM is a census of all US manufacturing establishments in the United States. The first year available to researchers is 1963. Starting in 1967, Census began performing the survey quinquennially in years ending in 2 and 7. Our baseline sample period consists of all CM years from 1963 to 1987. The CM provides plant-level data on the baseline measures of output (sales) and inputs (labor, energy) that we report. To track plants and firms across the years covered in our study, we employ the Longitudinal Business Database (LBD). The LBD has been carefully constructed by Census to ensure consistency across years for both plant and firm identifiers (Chow et al., 2021). The consistent identifiers allow us to observe when plants shut down. The firm identifier allows us to identify all plants owned by a common firm which allows us to calculate firm-level measures of our key variables and identify within firm reallocation across plants and geography.

To make our results comparable to the previous literature, we focus on the industries Greenstone (2002) labels as major emitters of Total Suspended Particulates. The industry groups are "Lumber and Wood Products", "Pulp and Paper", "Stone, Clay, Glass, and Concrete" and "Iron and Steel".[12] Becker and Henderson (2000), Greenstone (2002) and Greenstone, List, and Syverson (2012) argue that regulators target these pollution-intensive industries to bring counties back into attainment. To estimate the effects of the regulation across all manufacturing industries, we rely on public CBP data as described below.

[12]For our plant-level estimates, our sample consists only of plants in exactly the industries listed as major emitters of TSP in Table A2 in Greenstone (2002). At the county-level, our definition of major emitter is slightly broader in that we include all 3-digit industries that fall in those industry groups, some of which Greenstone excludes.

County-Sector Employment To estimate county-level impacts, we rely on county by 2-digit SIC sector employment data from the County Business Pattern (CBP) for the period 1967-1987. We use the data provided by Eckert et al. (2020) and Eckert et al. (2022).[13] Since we use the CBP across a time period where coverage expands sharply, we limit ourselves to county-sector cells with positive employment throughout the period 1967-1987.[14] This also limits the influence of very small county-sector cells on our estimates. Employment changes in these cells may be unduly influenced by reporting changes, such as whether multi-unit firms report all their employment to the location of the headquarter establishment.

5.2 Effect of Nonattainment on Regulated Firms

We start by revisiting the effects of 1970s CAAA regulations on plant-level outcomes. Our estimation sample consists of all plants that operate in polluting industries. We focus on the effects on incumbent plants by dropping plants not yet active in 1963. We estimate Poisson Pseudo-Maximum Likelihood (PPML) models of the form

$$y_{i(c,j),t} = \exp\left(\sum_{\tau=1963,\tau\neq 1967}^{1987} Treat_c \times 1\{t=\tau\}\beta_\tau + \mu_i + \mu_{jt} + \mu_{st}\right)\epsilon_{i(c,j),t} \tag{1}$$

where $y_{i(c,j),t}$ refers to outcome y (employment, sales) of plant i in county c and industry j. We impute $y_{i(c,j),t} = 0$ for all years after the plant exits, allowing us to account for regulation induced plant exit.

Our estimate is derived from comparing plants in initially regulated areas, $Treat_c = 1$, to those in unregulated areas. To ensure our control group is not differentially affected by other CAA regulations, we drop a small number of counties that are in nonattainment for pollutants other than TSP, but in attainment for TSP. Given our focus on within-firm leakage, we additionally exclude unregulated plants whose parent firm operates regulated plants in the same industry. A primary concern with equation (1) is that regulation affects heavily polluted areas, with higher population density and manufacturing employment. To

[13] Eckert et al. (2022) digitize the CBP for years prior to 1974 and Eckert et al. (2020) develop a methodology to impute missing employment cells.

[14] Figure 1 in Eckert et al. (2022) shows a significant jump in the number of available observations within this period. Most of these additional observations are insignificant in terms of their contribution to overall employment. We obtain very similar effects in terms of size and significance when we estimate the effects of nonattainment on the full panel.

ensure our estimates are not driven by these differences, we include plant, industry-by-year, state-by-year, initial size decile-by-year and initial labor productivity decile-by-year fixed effects. Standard errors are clustered at the county-level.

Figure 1 shows results for employment and sales. Prior to the passage of the CAA, treatment and control groups trend similarly. After the regulation, employment and sales of regulated plants fall relative to unregulated plants. The long-run effect in 1987 amounts to a 26% decline in employment and a 30% decline in sales.[15]

Next, we study whether these large relative effects reflect extensive margin adjustments through exit or downsizing along the intensive margin. Using the same sample of incumbent plants, we estimate a linear probability model for plant exit:

$$\mathbb{I}[exited_{i(c,j),t}] = \sum_{\tau} Treat_c \times 1\{t = \tau\}\beta_\tau + \beta_0 X_{i,1963} + \mu_{jt} + \mu_{st} + \epsilon_{i(c,j),t}. \tag{2}$$

Intuitively, we compare exit rates between plants in regulated and unregulated areas, controlling for state and industry-by-year fixed effects. One important difference between the regression models (1) and (2) is that it is not possible to control for time-invariant differences in the propensity to exit via unit fixed effects. To address this issue, we control for plant-level employment in 1963, $X_{i,1963}$, when all plants in our sample were active and once again control for initial labor productivity decile-by-year fixed effects.

Figure 2 reports results of a version of the regression model (2) that adds a multiunit (MU) plant indicator interaction term. While there is no initial difference in the propensity to exit among either group of plants, regulated MU plants are 15 percentage points more likely to have exited the industry by 1987. Regulation does not affect the likelihood of exit for single-unit plants. This differential response by firm type is consistent with MU firms shutting down production at regulated plants and shifting it to unregulated sister plants.

The persistence and size of the effects in Figures 1 and 2 suggest that nonattainment significantly restricts plants' growth trajectory, consistent with regulation becoming more stringent with the passing of the 1970 and 1977 amendments to the Clean Air Act. While we have made efforts to create a "cleaner" control group, the estimates provided here should still be interpreted as evidence of a *relative* effect of nonattainment. According to the

[15]Since we use PPML to estimate equation (1), these effects should be interpreted as percent change in the mean and not the mean percent change (Chen and Roth, 2023).

conceptual framework laid out in Section 4, the estimated declines in employment and sales likely overstate the effect of the policy on plants in regulated counties. This bias arises in our context because economic activity likely reallocates towards attainment counties, violating the stable unit treatment value assumption (SUTVA).

To study this reallocation, we test whether multi-unit firms offset declines among regulated plants by increasing production at their unregulated plants. We consider a sample of firms active in both regulated and unregulated counties, as measured by the location of their plants prior to the policy. We use PPML to estimate the following specification

$$y_{f(j),t} = \exp\left(\sum_{\tau=1963,\tau\neq 1967}^{1987} Treat_f \times 1\{t=\tau\}\beta_\tau + \mu_{jt} + \mu_f\right)\epsilon_{i(c,j),t}, \tag{3}$$

where $y_{f(j),t}$ refers to the total activity of firm f across all its unregulated plants in industry j. Activity is measured in terms of employment, sales, cost of fuels and number of plants. $Treat_f \in (0,1)$ denotes the share of pre-regulation firm-industry employment located in eventually regulated counties. This specification isolates shifting of activity between plants producing similar products in a given firm. Since all firms in this sample operate a regulated plant, we test whether firms that are more strongly exposed to the regulation increase activity among their unregulated plants.

Even if nonattainment is exogenous conditional on fixed effects, firm level exposure to regulation at other plants may not be random in equation (3): Large firms may disproportionately locate in more densely populated, regulated areas. If these firms are also on different growth trajectories at their unregulated plants, this can create omitted variable bias. To address this concern, we construct pseudo-exposure measures following the approach outlined in Borusyak and Hull (2023). We repeatedly randomize regulation across counties with ex ante characteristics similar to those that were in fact regulated.[16] We then compute firms' pseudo-exposure as the average across these counterfactuals, interact it with year fixed effects, and include it as a control variable. As before, we also control for industry-year and firm fixed effects. Standard errors are clustered at the firm-level.

Figure 3 shows that exposure to regulation leads to significant increases in employment and sales at unregulated plants. There was also short-run increase in the number of unregu-

[16] Appendix E describes the exact algorithm we use to compute counterfactual regulation assignments.

lated plants for the more exposed firms. Within firm leakage effects for sales and total cost of fuel are shown in the panel B of Figure 3. After regulation, both sales and fuel expenditures grow more strongly in more exposed firms. Similar to the effects of regulation unfolding over time, these effects are highly persistent. In 1982, a 10% increase in exposure leads to a 4% increase in employment and a 7% increase in sales.[17] In Appendix Figure A1, we show robustness of these results to using a discrete treatment variable that equals one for firms with $Treat_f > Median(Treat(f))$.

To summarize the results, Figure 4 plots the average change in the share of firm employment, sales, number of plants and cost of fuels that is accounted for by plants in regulated counties. The sample consists of firms that were active in both nonattainment and attainment areas prior to the policy. The share of firm activity carried out in nonattainment areas was stable between 1963 and 1972, but declines by roughly 3 percentage points after the regulation. We have identified three drivers to this shift: declines in sales and employment among regulated plants, exit of regulated plants, and increases in economic activity among unregulated plants.

5.3 County-level Effects of Nonattainment Status

To study the effects of nonattainment at the county-level, we draw on recently digitized CBP data provided by Eckert et al. (2022).[18] The county-level analysis complements our plant-level estimates in Section 5.2. By studying effects on total employment at the county by 2-digit sector level, we additionally account for effects of the policy on plant entry. An advantage of the plant-level approach is that we can better account for compositional differences between the types of plants that operate in nonattainment and attainment counties.

We use the following event-study specification to estimate the effects of nonattainment

[17] We obtain these by exponentiating the event study coefficients for sales and employment and multiplying both by 0.1.

[18] The CBP is an unbalanced panel at the county-sector level, but our results are robust to estimating effects on a balanced panel of county-sectors.

on county-sector employment via PPML:

$$\text{Employment}_{cjt} = \exp\left(\sum_{\substack{\tau=1967 \\ \tau\neq 1970}}^{1987} 1\{t=\tau\} \times (\text{Treat}_c\beta_\tau + IE_{cj}\gamma_\tau + X_{cj}\delta_\tau) + \mu_{cj} + \mu_{jt}\right)\epsilon_{cjt}. \tag{4}$$

We separately estimate the effect of own exposure to regulation via $Treat_c$ as well as through indirect exposure to regulation in other nearby counties

$$IE_{cj} = \sum_{k\neq c}^{K} \frac{D_{ck}^{-\delta}}{\sum_{k'\neq c}^{K} D_{ck'}^{-\delta}} \text{Employment}_{kj1970} \cdot Treat_k,$$

where D_{ck} is distance between county c and k and δ is a decay parameter determining the relative weight on counties at different distances.[19] Intuitively, indirect exposure is large if a county is located close to other regulated counties that also have a lot of employment in sector j. This approach to modeling spatial leakage is inspired by Adao, Arkolakis, and Esposito (2025) and we follow their work in additionally controlling for $X_{cj} = \sum_{k\neq c}^{K} \frac{D_{ck}^{-\delta}}{\sum_{k'\neq c}^{K} D_{ck'}^{-\delta}} \text{Employment}_{kj1970}$ to capture agglomeration or business stealing effects. Indirect exposure across counties may be subject to similar omitted variable concerns as the within firm leakage. We therefore include a county-level pseudo-exposure measure to control for the effect of non-random exposure. To control for differences between attainment and nonattainment counties, we also add county-sector, as well as sector- and state-year fixed effects and the interaction of (log) initial population with year effects. We cluster our standard errors at the state-level since the indirect exposure variable may induce spatial correlation in residuals across counties.

Figure 5 plots the county-level effects of nonattainment $\hat{\beta}_\tau$ on polluting industry employment (SIC codes 24, 26, 32 and 33). By 1987, employment declines by 25.2% relative to attainment counties, in line with effects estimated at the plant-level. Figure 6 presents our estimates for spatial leakage $\hat{\gamma}_\tau$ for a spatial decay of $\delta = 5$, following the baseline value used by Adao, Arkolakis, and Esposito (2025). Counties more heavily exposed to the regulation through their neighbouring counties see increases in employment. The estimated effects imply that a county at the 75th percentile of the empirical distribution of the exposure variable

[19] Distances between counties are taken from the NBER County Distance Database.

IE_{cj} sees a 2.4% increase in employment relative to a county at the 25th percentile. Figure A2 shows that these spatial leakage effects are robust to different values of spatial decay. Results are robust to any $\delta \in \{1, 3, 5\}$ or using a simpler spatial weight that is equal to one for employment within 40 miles of a given county and zero otherwise.

These county-level results complement the leakage along firm ownership networks by also including leakage driven by intra-national trade.

5.4 Further Results

Broader Employment Effects. Consistent with prior literature, we estimated the effects of nonattainment by studying the response of industries labeled as polluting by Greenstone (2002). Figure A3 shows effects of the regulation on non-polluting industries as well as total manufacturing employment. Employment declines in non-polluting industries are somewhat smaller than in polluting industries at around 10%, with slightly larger effects on total manufacturing employment. These results illustrate that the effects of nonattainment are not offset by reallocation of workers to less polluting industries. Instead, they are consistent with regulation negatively affecting the entire manufacturing sector. Figure A3 relates our results to some alternative estimators of the effects of nonattainment in Greenstone (2002), which relies on a triple-difference design comparing clean and dirty industries, before and after regulation, across attainment and nonattainment counties. Figure A3 illustrates this type of comparison would imply smaller effects of nonattainment since non-polluting industries decline too. We believe this comparison constitutes a lower bound of the effects of nonattainment because non-polluting industries remain a plausible target for regulators: Figure A4 plots the share of Toxic Release Inventory Plants that have a permit under a regulatory program related to the Clean Air Act. This proxy for regulatory activity is relatively uniformly distributed across industries, in line with Figure II in Walker (2013).

Effects on Wages. We also consider the effect of regulation on manufacturing wages. To do so, we use decadal IPUMS census data to construct composition adjusted average log wages at the commuting zone level.[20] A commuting zone is considered treated if any

[20] We follow the approach in Suárez Serrato and Wingender (2014) to estimate these price indexes.

of the counties within the commuting zone is in nonattainment (cf. Currie, Voorheis, and Walker (2023) for a similar approach to defining treatment). Figure A5 shows no statistically significant effect on average wages.

Effects on TSP Pollution. We provide new estimates of the effect of nonattainment on long-run TSP pollution levels. Figure A6A shows that nonattainment decreases TSP pollution. We estimate short-run effects close to those in Isen, Rossin-Slater, and Walker (2017), but our estimated long-run decline is roughly 50% larger. Analogous to the employment leakage in Figure 6, Figure A6B shows our estimates of pollution leakage. Pollution leakage are a function of two competing forces: lower pollution in regulated counties also means less pollution can end up in neighbouring counties through atmospheric transport. On the flip side, reallocation of economic activity increases pollution in neighbouring counties. We find these two channels roughly offset with positive, but statistically insignificant pollution leakage.

6 Quantitative Analysis

We now outline a model of multi-region trade and production with multi-plant firms that matches the production activity of pollution-intensive manufacturing industries across space. We structurally estimated this model and show it can reproduce the reduced-form results in Section 5. We then use this model to guide our interpretation of aggregate and environmental implications from the reduced-form difference-in-difference estimates of the Clean Air Act regulations.

6.1 Model

Demand The economy has N locations. Each location m has a representative consumer with preferences given by a Cobb-Douglas aggregator across sectors $s = (clean, dirty)$.

$$U_m = \prod_s (c_m^s)^{\alpha^s}, \quad \text{where} \quad \sum_s \alpha^s = 1,$$

and where the sectoral consumption

$$c_m^s = \left(\int_{\Omega_m^s} q_m^s(\omega)^{\frac{\eta-1}{\eta}} d\omega \right)^{\frac{\eta}{\eta-1}}. \tag{5}$$

$q_m^s(\omega)$ is the quantity that the consumer purchases from firm ω and Ω_m^s is the set of firms in sector s selling to market m. The parameter η governs the elasticity of substitution across varieties within sector.

Utility maximization yields the following individual firm demand in market m

$$q_m^s(\omega) = p_m^s(\omega)^{-\eta} \frac{I_m^s}{(P_m^s)^{1-\eta}} \equiv p_m^s(\omega)^{-\eta} A_m^s, \tag{6}$$

where

$$P_m^s = \left[\int_{\Omega_m^s} p_m^s(\omega)^{1-\eta} \right]^{\frac{1}{1-\eta}}. \tag{7}$$

Given consumer expenditure I_m, the sector expenditure is $I_m^s = \alpha^s I_m$, and the market-specific aggregate price is defined as $P_m = \prod_s (P_m^s/\alpha^s)^{\alpha^s}$. Since each sector s is separable in terms of their consumer expenditure I_m^s and price index P_m^s, we develop the firm production and sales decisions abstracting from s below.

Technology Each firm ω is defined by its core efficiency ϕ and a set of locations with active plants Z. Firm ω assemble her variety in market m with a unit continuum of inputs shipped from its production locations such that[21]

$$q_m(\omega) = \left[\int_0^1 q_m(\omega, j)^{\frac{\eta-1}{\eta}} dj \right]^{\frac{\eta}{\eta-1}}$$

Labor is the only input in production with constant return-to-scale technology. For each *input* j, there is a set of IID random productivity draw ν_l associated with each of her plants $l \in Z$.

$$y_l(\omega) = (1 - a_l(\omega))\nu_l(\omega) n_l(\omega)$$

where y_l and n_l are respectively the output and labor input. Following Shapiro and Walker (2018), we assume that $a_l(\omega)$ is the plant abatement effort to reduce the pollution emission

[21] Without loss of generality, assume these inputs $j \in [0, 1]$.

$e_l(\omega)$ with an elasticity ϵ_s:

$$e_l(\omega) = (1 - a_l(\omega))^{1/\epsilon_s} \nu_l(\omega) n_l(\omega)$$

Substitute $1 - a_l(\omega)$ into the production function, we obtain the pollution-augmented production function

$$y_l(\omega) = \tilde{\nu}_l(\omega) e_l(\omega)^{\epsilon_s} n_l(\omega)^{1-\epsilon_s} \quad \tilde{\nu}_l(\omega) \equiv \nu_l(\omega)^{1-\epsilon_s}$$

As a result, the unit cost of production of firm ω at location l is $c_l(\omega) = \frac{r_l^{\epsilon_s} \bar{w}_l^{1-\epsilon_s}}{\tilde{\nu}_l(\omega)} \equiv \frac{w_l}{\tilde{\nu}_l(\omega)/(r_l^{\epsilon_s})}$, where r_l denotes the shadow cost of environmental regulation and w_l is the effective location-specific labor cost. As is clear from this setup, stricter environmental regulation at location l increases r_l and reduces both the emission $e_l(\omega)$ and the unit cost efficiency $\tilde{\nu}_l(\omega)/(r_l^{\epsilon_s})$.

The productivity distribution $\tilde{\nu}_l$ is assumed to be IID Fréchet (which depends on both plant efficiency ϕ_l and local condition $\bar{T}_l$). As we will specify in section 6.2, ϕ_l depends on core efficiency ϕ and geography l deterministically.

$$Pr(\tilde{\nu}_l \leq x) = exp(-(\phi_l \bar{T}_l)^{\theta}(x)^{-\theta}).$$

Given the assumption of production technology, the cost distribution of sourcing from each location remains Fréchet with $T_l \equiv \bar{T}_l/(r_l^{\epsilon_s})$:

$$Pr\left(\frac{w_l \tau_{lm}}{\tilde{\nu}_l/(r_l^{\epsilon_s})} \leq c\right) = 1 - exp\left(\left(\frac{w_l \tau_{lm}}{\phi_l T_l}\right)^{-\theta} c^{\theta}\right).$$

The firm chooses to ship each input j to market m from its lowest cost location $l \in Z$. Given that Fréchet is max-stable, we have its minimal cost of input $c_m(\omega, j)$ shipping to market m distributed as

$$G_m(c|\phi, Z) = 1 - exp\left(-\left(\sum_{l \in Z} \frac{w_l \tau_{lm}}{\phi_l T_l}\right)^{-\theta} c^{\theta}\right).$$

We can obtain the expected cost of serving market m for firm ω per unit of shipment as

$$\begin{aligned} c_m(\phi, Z) = \left[\int_0^1 c_m(\omega, j)^{1-\eta} dj\right]^{\frac{1}{1-\eta}} &\equiv \left[\int_0^{\infty} c^{1-\eta} dG_m(c|\phi, Z)\right]^{\frac{1}{1-\eta}} \\ &= \underbrace{\Gamma\left(\frac{\theta + 1 - \eta}{\theta}\right)^{\frac{1}{1-\eta}}}_{\Gamma_\theta} \left(\sum_{l \in Z} \left(\frac{w_l \tau_{lm}}{\phi_l T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}. \end{aligned} \tag{8}$$

It is useful to note that the environmental regulation can potentially change the effective location productivity T_l. As we show below, these changes then impact both the intensive margin of inter-region trade and the marginal benefit of having an additional plant in each location l.

Profit Maximization Given the assumption of monopolistic competition in each product market, each firm sets a constant markup of $\frac{\eta}{\eta-1}$ for all its products. Firm ω's price for market m is then

$$p_m(\phi, Z(\omega)) = \left(\frac{\eta}{\eta-1}\right) c_m(\phi, Z(\omega)) = \left(\frac{\eta}{\eta-1}\right) \Gamma_\theta \left(\sum_{l \in Z(\omega)} \left(\frac{w_l \tau_{lm}}{\phi_l T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

Each firm has sales at market m of

$$s_m(\phi, Z(\omega)) = \underbrace{\frac{I_m}{P_m^{1-\eta}}}_{A_m} p_m(\phi, Z(\omega))^{1-\eta}.$$

Firms choose the optimal combination of locations Z, given its productivity ϕ, headquarter location l, and the the set of IID random fixed costs $\vec{f}_{l'} \sim G_f, \forall l' \neq l$ to maximize profits as follows

$$\pi(\phi, l(\omega), \vec{f}_{l'}(\omega)) = \max_{Z \in \mathcal{Z}} \frac{1}{\eta} \sum_m s_m(\phi, Z(\omega)) - \sum_{l' \in Z(\omega), l' \neq l} f_{l'}(\omega), \tag{9}$$

where $Z(\omega)$ always includes headquarter location l and firms pay fixed costs to operate additional plants.

To take our model to the observed data of plant-level sales, we also characterize the share of sales to market m that are sourced from $l \in Z(\omega)$:

$$\mu_{lm}(\phi, Z(\omega)) = \frac{(w_l \tau_{lm})^{-\theta} (\phi_l T_l)^\theta}{\sum_{k \in Z(\omega)} (w_k \tau_{km})^{-\theta} (\phi_k T_k)^\theta}. \tag{10}$$

As a result the total shipments from a firm's plants in location $l \in Z(\omega)$ are given by

$$r_l(\phi, Z(\omega)) = \sum_m s_m(\phi, Z(\omega)) \times \mu_{lm}(\phi, Z(\omega)).$$

Entry A large pool of ex ante identical potential entrants decide whether to operate in each industry. They incur an entry cost to take random draws of their productivity $\phi \sim G_\phi$, their headquarter location l, and the set of IID random fixed costs $\vec{f_{l'}} \sim G_f, l' \neq l$ to operate another plant in any additional locations. The free entry condition will rationalize the mass of active entrants where the entry cost equals the expected profit. We denote the total mass of entrants as E and the realized location-specific number of firms as $E_l = \mu_l E$.

Equilibrium Given $w_l, I_m, T_l, \tau_{lm}, G_f, G_\phi, \forall m, l = 1, ..., N$, the dirty industry equilibrium is a vector of price indexes P_m, allocations for the representative consumer $q_m(\omega)$, firm prices $p_m(\phi, Z(\omega))$ for each $m = 1, ..., N$ and their location choices $Z(\omega)$ such that

1. Equation (6) solves the consumer's optimization problem;
2. P_m satisfies equation (7);
3. and $p_m(\phi, Z(\omega))$ and $Z(\omega)$ solve the firm's profit maximization problem (9).[22]
4. Free entry such that

$$\int_0^\infty E_{\vec{f}_{l'}}[\pi(\phi, l, \vec{f_{l'}})]\mu_l dG_\phi = f_E$$

where μ_l is the exogenous probability that an entrant is headquartered at location l.

This model abstracts from general equilibrium wage changes since the dirty manufacturing industry remains a moderate share of aggregate labor demand and is also justified by the muted reduced-form wage response to regulation in section 5.4. It is nevertheless rich enough to capture *geographic* patterns that is important to examine output and pollution leakages across space within the industry. After quantifying the model, we show that we can implement the regulation in our model by imposing nonattainment status on a large number of local areas. Doing so allows us to find the implied costs of the regulation that rationalize the decline of employment in nonattainment regions relative to attainment regions. As we show in Section 7, while some of the intuitions from our simpler model continue to hold, the economic realism of the quantitative model yields a more precise quantitative account of the economic costs of the regulation in both attainment and nonattainment areas.

[22] Since we are interested in the response of a subset of manufacturing industries to environmental regulations, we define an industry equilibrium where wages in each location are taken as given.

Solving the Multi-Unit Firm Location Problem Given the local and place-based nature of nonattainment areas, a key goal of our analysis is to model a large number of locations that can realistically correspond to attainment and nonattainment areas. In practice, we use the 1990 definition of Commuting Zones (CZs) that includes 722 CZs, excluding CZs in Alaska and Hawaii. In this setting, the number of location combinations that firms may choose from is a staggering 2^{722}.[23]

A factor that complicates solving this large combinatorial choice problem is the fact that, in theory, the location decisions of different plants in a firm can be interconnected. To see this, write the total payoff of the firm with core productivity ϕ and operating locations Z as

$$\begin{aligned}\pi(\phi, Z) &= \frac{1}{\eta}\left(\frac{\eta}{\eta-1}\Gamma_\theta\right)^{1-\eta}\sum_m A_m\left[\left(\sum_{l\in Z}\left(\frac{\tau_{lm}}{\phi_l T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}\right]^{1-\eta} - \sum_{l\in Z} f_l \\ &\equiv \tilde{\eta}_\theta \sum_m A_m\left[\left(\sum_{l\in Z}\left(\frac{\tau_{lm}}{\phi_l T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}\right]^{1-\eta} - \sum_{l\in Z} f_l, \qquad (11)\end{aligned}$$

where $\tilde{\eta}_\theta = \frac{\eta^{-\eta}}{(\eta-1)^{1-\eta}}(\Gamma_\theta)^{1-\eta}$. It is clear from the payoff function that more productive firms have larger payoffs. In addition, more productive firms also operate in more locations, on average. However, the choice of locations Z depends on the set of trade costs τ_{lm} and is a combinatorial problem that is burdensome to solve. To make this location choice problem computationally tractable, we leverage the submodularity property of firm profits and employ squeezing and branching techniques, following the approach of Arkolakis, Eckert, and Shi (2023).

6.2 Parameterization and Estimation

Parameterization We assume perfect labor mobility and normalize $w_l = w = 1$ across locations. Our model equilibrium solution then depends on a rich set of local primitives $I_m, \mu_l, T_l, \tau_{lm}, \forall m, l = 1, ..., N$, and random technology distributions G_ν, G_ϕ, and fixed cost distribution G_f. We parametrize bilateral trade costs as a function of origin–destination distance,

$$\tau_{lm} = \text{dist}_{lm}^{\beta_\tau}.$$

[23] Note that 2^{722} is more than 220 quadrillion times larger than a googol squared.

The idiosyncratic plant–location–specific productivity shock ν_l follows a Fréchet distribution with shape parameter θ and location-specific scale shifters T_{AA} for attainment areas and T_{NAA} for nonattainment areas. We allow T_l to differ across locations only through these two shifters, which over-identifies the model. Firm headquarter productivity ϕ_h is assumed to follow a log-normal distribution, $\log \phi_h \sim \mathcal{N}(0, \sigma_\phi^2)$. Productivity at an additional plant located in l obeys a flexible distance-based efficiency decay,

$$\phi_l = \phi_h \, \text{dist}_{lh}^{\beta_\phi}.$$

This specification is motivated by the strong within-firm skewness in production observed in the micro data. The random fixed cost of operating an additional plant is $\log f_l \sim \mathcal{N}(\mu_f, \sigma_f)$. Finally, we will also need to infer the regulatory impact of local productivity ΔT_{NAA}. To sum up, after normalizing $T_{AA} = 1$, we use simulated indirect inference to estimate the 8 parameters $\Theta = [T_{NAA}, \Delta T_{NAA}, \beta_\tau, \theta, \sigma_\phi, \beta_\phi, \mu_f, \sigma_f]$.

To initiate the simulation of our model, we will also need to calculate local primitives I_m and μ_l from the data. In the absence of granular commuting zone-level spending data, we approximate I_m by combining county-level personal income from the BEA with the state-level expenditure on the four polluting manufacturing sectors from the Commodity Flow Survey. Letting s be state and c county, we compute

$$I_m^s = \sum_{c \in m} \frac{\text{Income}_c}{\sum_{c \in s} \text{Income}_c} I^s,$$

where I^s is state-level expenditure on dirty manufacturing from the Commodity Flow Survey and Income_c is county-level income from the BEA.[24] The location l headquarter probability μ_l is assumed to be proportional to each CZ population.

Identification Although all structural parameters are jointly estimated, different moments provide differential identifying power across parameters. Table 1 summarizes the primary sources of identification for each parameter. The relative productivity premium of nonattainment areas, T_{NAA}/T_{AA}, is identified from their pre-regulation employment share. The

[24] Both spending and county-level income are for the year 2002, which is the earliest year the state-to-state CFS is available at the industry-level. While commuting zones sometimes cut across state borders, counties are nested within both commuting zones and states.

Table 1: Summary of Parameters

Parameter	Functional Form	Source/Targeted Moments
Calibrated Parameters		
Demand elasticity	$\eta = 4$	
Elasticity of c w.r.t. regulation	$\epsilon = 0.05$	Shapiro and Walker (2018)
Estimated Parameters		
Initial NAA productivity premium	T_{NAA}/T_{AA}	NAA employment share
Regulation productivity shock	ΔT_{NAA}	Dif-in-Dif on plant output
Idiosyncratic cost distribution	Fréchet θ	Dif-in-Dif on firm leakage
Trade cost	$\tau_{lm} = dist_{lm}^{\beta_\tau}$	distance gravity in CFS
Firm HQ productivity	$\phi_h \sim \log N(0, \sigma_\phi)$	MU share of total sales
Within-firm productivity decay	$\phi_l = \phi_h \, dist_{l,h}^{\beta_\phi}$	Within-firm concentration
Fixed cost of add. plant	$f_l \sim \log N(\mu_f, \sigma_f)$	MU share / plants per firm

regulatory impact on productivity, ΔT_{NAA}, is identified from the difference-in-differences estimate of the plant-level output response. The Fréchet shape parameter θ governs within-firm production reallocation and is therefore identified from the DID estimate of firm-level leakage. Using state-to-state commodity flow data for dirty manufacturing industries, we estimate the distance elasticity of trade, β_τ, which ensures that the model-implied trade flows are consistent with the gravity relationship observed in the data. The remaining parameters are primarily disciplined by patterns of multi-unit production in the Census of Manufacturers. In particular, the fraction of multi-unit firms, their sales share, and the distribution of plants per firm jointly identify the firm productivity dispersion parameter σ_ϕ and the fixed cost distribution (μ_f, σ_f). Finally, the within-firm productivity decay parameter β_ϕ is identified from the concentration of multi-unit firm sales in the largest plant. We use the indirect inference to estimate $\hat{\Theta}$ that minimizes the criterion function $[m_d - m(\Theta)]' W [m_d - m(\Theta)]$, where $m(\Theta)$ include model simulation-based moments and regression coefficients.

Parameter Estimates and Model Fit Table 2 reports the parameter estimates and the model fit. Our estimate shows that the nonattainment areas were about 5% more productive before the CAAA regulations, but the regulation cut this premium by about a half. The

Fréchet parameter $\theta = 5.03$ ends up to be substantially larger than $\eta - 1 = 3$, so the within-firm relocation effect effect is stronger than the product market substitution. This indicates that the multi-unit firms in the U.S. dirty manufacturing re-inforces the spatial leakage of the regulation. The firm productivity distribution is dispersed $\sigma_\phi = 0.63$ and justifies the large fraction of sales accounted for by the multi-unit firms despite their tiny share among all the firms. The estimated distance elasticity of productivity decay is modest in magnitude ($\beta_\phi = -0.09$). Trade flows exhibit a strong distance gradient, consistent with standard gravity patterns. This suggests that, while distance matters for within-firm production allocation, the primary role of distance in shaping trade outcomes likely operates through trade costs rather than internal productivity decay.

The table also shows that the model successfully matches the data moments. To further check if the model captures the geographical features accurately, we compare the spatial distribution of sales in the data and model. Figure 8 shows the maps of production in the data and the model in the initial equilibrium. The correlation between the model-simulated and actual production is 79%. We also report several untargeted data moments in Table 2. They include the sales share accounted for by the largest 1%, 5%, 10%, and 25% dirty industrial firms, as well as the within-firm sales HHI for multi-unit firms. Overall, the model-implied moments align closely with these untargeted data moments.

Interpreting Difference-in-Differences Estimates As discussed in Section 4, the coefficients from our difference-in-differences estimates of equations 1 and 2 capture a relative effect between treated and control plants. Our model allows us to further decompose the direct effect of regulation (column 2 in Table 3) into distinct impacts for plants located in regulated and unregulated areas. This decomposition reveals an 8.7% decline in sales for plants in regulated locations, which accounts for approximately 60% of the estimated difference-in-differences effect, alongside a 5.1% increase in sales for plants in unregulated locations, accounting for the remaining 40%. Consistent with the theoretical insights in Section 4, these results indicate that conventional difference-in-differences estimates overstate the negative impact of regulation on economic activity in nonattainment areas by failing to account for offsetting gains elsewhere. At the same time, the results highlight that attainment areas

Table 2: Parameter Estimates and Model Fit

	Estimate	**Standard Error**
Parameters		
Initial NAA productivity premium T_{NAA}/T_{AA}	1.053	0.027
Regulatory productivity shock ΔT_{NAA}	−0.035	0.009
Idiosyncratic cost distribution (Fréchet θ)	5.03	0.422
Trade cost β_τ	0.436	0.012
Firm HQ productivity dispersion σ_ϕ	0.631	0.023
Within-firm productivity decay β_ϕ	−0.090	0.007
Fixed cost of additional plant μ_f	1.830	0.103
Fixed cost of additional plant σ_f	1.173	0.054
	Data	**Model**
Targeted Moments		
MU share	0.029	0.030
Average number of plants per MU	4.15	4.19
Share of production from MU	0.663	0.663
Average sales share of largest plant among MU	0.560	0.565
Share of employment in NAA	0.663	0.664
State-to-state distance elasticity of trade	−2.08	−2.06
Plant-level direct effect	−0.139	−0.137
Firm-level leakage effect	0.126	0.127
Untargeted Moments		
Sales Share of Top 1% Firms	0.595	0.542
Sales Share of Top 5% Firms	0.801	0.742
Sales Share of Top 10% Firms	0.878	0.829
Sales Share of Top 25% Firms	0.951	0.931
Average within-firm HHI (sales) among MU	0.464	0.452

experience economically meaningful benefits from the regulation. Meanwhile, notice that our model also performs reasonably well explaining most of the difference-in-difference estimates (within-firm reallocation and exit).

Equipped with all these parameter estimates, we next use our model to quantify the geographical economic and environmental impact of the Clean Air Act Regulation in section

Table 3: Difference-in-Differences Estimates in Data and Model

	Within Firm Reallocation	Direct Effect		Spillover Effect	
		Overall	MU Exit	Continuous	Discrete
A. Data vs. Model		(Targeted)		(Targeted)	
Empirical	-0.0308	-0.1389	0.1052	0.1258	0.1346
	(0.0060)	(0.0410)	(0.0419)	(0.0643)	(0.0654)
Model	-0.0518	-0.1373	0.0580	0.1267	0.1053
	(0.0007)	(0.0049)	(0.0037)	(0.0195)	(0.0283)
B. Decomposition					
Change in Treated		-0.0867			.
Change in Control		0.0506			.

Notes: Within firm reallocation and direct effect (MU exit) are weighted using initial firm/plant employment. Spillover effect (continuous) reports the implied effect of firms with regulation exposure from the 1st to the 3rd quantile. We target the overall direct effect and the continuous spillover estimates in our structural estimation. Other difference-in-differences estimates are untargeted in our estimation.

7.

7 Trading Off the Economic and Pollution Effect of Environmental Regulations

We now use the quantitative model to evaluate the aggregate and spatial consequences of the Clean Air Act. Section 7.1 characterizes regional and national price changes, which summarize the economic cost of the regulation. Section 7.2 examines the role of multi-unit firms in shaping spatial reallocation and price responses. Section 7.3 quantifies the resulting changes in pollution and mortality, and Section 7.4 combines economic and environmental effects in a welfare calculation. Together, these exercises provide a unified assessment of the regulation's economic costs and environmental benefits.

7.1 Regional and Aggregate Price Changes

To quantify the economic cost of the regulation, we begin by examining changes in regional price indexes. In the model, price indexes directly measure the consumption costs of the reg-

ulation. Given fixed expenditure, real consumption is determined by dividing expenditure by the market price. Model simulations indicate that prices increase in most locations, including both nonattainment and attainment areas. Prices in attainment areas also rise, even though output increases there, because these markets source from regulated locations that have experienced productivity losses. Although most locations experience price increases, 45 out of 722 commuting zones exhibit price declines. This decline is driven by increases in the production of the home or adjacent locations, which save on trade costs.

Figure 9 plots the percentage changes in prices for each commuting zone. The West Coast and Mid-Atlantic regions experience the largest price increases, whereas central areas of the country face smaller increases or even price declines. To summarize across locations, we compute the expenditure-weighted average of $\Delta \log P_m$, which implies a national price increase of 2.02%.

7.2 Multi-Unit Firms and the Effects of Regulation

Our model allows us to more precisely quantify the role of within-firm leakage in the reallocation of production to unregulated areas. To isolate the quantitative importance of this within-firm channel, we consider a counterfactual specification of the model that shuts down the scope for within-firm substitution while keeping other features of the environment unchanged. This exercise allows us to assess how much of the observed reallocation and aggregate price response is driven specifically by multi-unit production networks.

We implement this counterfactual by recalibrating the model with $\theta = 3.01 \approx \eta - 1$, which effectively shuts down within-firm inter-dependence. To see this, note that in Equation 11, both the intensive margin (production allocations) and the extensive margin (plant location decisions) become separable across locations when the strength of spillovers within a firm (governed by θ) coincide with the strength of market-level spillovers (governed by $\eta - 1$). For this reason, plants behave like single-unit firms when $\theta = \eta - 1$. All other parameters are re-estimated to match the initial equilibrium and the empirical direct effect. Relative to the baseline, substitution across plants within a firm is sharply limited, leading to weaker extensive-margin adjustment across locations. Consequently, achieving the same direct effect requires a larger productivity shock, which increases from 3.5% to 5.1%.

Table 4: Effects Under Alternative Substitution Parameters

	ΔT_{NAA}	Direct Effect	MU Exit Effect	Spillover Effect	Sales Change: Non-Attainment Total	Sales Change: Non-Attainment Exit Share	Sales Change: Attainment Total	Sales Change: Attainment Entry Share
Baseline	-0.035	-0.137	0.058	0.127	-0.083	0.422	0.164	0.625
		(0.005)	(0.004)	(0.020)				
No MU Linkage	-0.051	-0.139	0.004	0.043	-0.071	0.036	0.138	0.497
		(0.001)	(0.001)	(0.017)				

Notes: The table reports model-implied effects under alternative values of the substitution parameter θ.

As shown in Table 4, extensive-margin responses are heavily attenuated. The multi-unit exit effect falls from 5.8% to 0.4%. With within-firm reallocation muted, plants of regulated firms located in unregulated regions respond similarly to those of unregulated firms, substantially weakening firm-level spillovers as an adjustment channel. Consistent with this mechanism, the estimated spillover effect is much smaller: the inter-quantile range effect declines from 13% in the baseline ($\theta = 5.03$) to 4% when $\theta = 3.01$.

Although both specifications are calibrated to match the same direct effect, they imply different aggregate and spatial price responses. Without within-firm reallocation, less production shifts toward unregulated regions. To match the direct effect, the model requires a larger negative productivity shock, which generates a stronger increase in prices. The expenditure-weighted average of $\Delta \log P_m$ rises from 2.02% to 2.63% relative to our baseline. Intuitively, this simulation also shows how the within-firm substitution parameter θ is pinned down by the within-spillover effect.

In addition to resulting in a larger price increase, this alternative calibration changes which locations experience price increases as a result of the regulation. Figure 10 illustrates the resulting spatial heterogeneity by plotting CZ-level differences in price changes between the low- and high-substitution cases. Most CZs exhibit positive differences, indicating larger price increases when within-firm reallocation is shut down. A smaller subset of regions—primarily in the Mountain West and parts of the central United States—exhibits negative differences.

While the alternative parameterization highlights how multi-unit firms shape aggregate outcomes, it does not reveal which specific adjustment margins are responsible for these differences. To better understand the mechanisms at work, we decompose the change in regional sales into three equilibrium channels: the direct productivity shock, firms' endogenous reconfiguration of plant networks, and general-equilibrium price responses. This decomposition clarifies how shutting down within-firm substitution alters not only the magnitude of reallocation, but also the relative importance of the underlying adjustment margins.

We decompose changes in sales in NAA and AA regions through three equilibrium channels: the productivity shock, plant configuration, and prices. Let $y_r(T, Z, P)$ denote total sales in region $r \in \{\text{NAA}, \text{AA}\}$, where T captures location-specific productivity, Z summarizes firms' plant configurations and production networks, and P denotes equilibrium prices. Comparing the post-shock equilibrium (T_1, Z_1, P_1) to the pre-shock equilibrium (T_0, Z_0, P_0), we express the total change in sales as

$$\begin{aligned} y_r(T_1, Z_1, P_1) - y_r(T_0, Z_0, P_0) = & \underbrace{y_r(T_1, Z_0, P_0) - y_r(T_0, Z_0, P_0)}_{\text{productivity effect at baseline choices}} \\ & + \underbrace{y_r(T_1, Z_1, P_0) - y_r(T_1, Z_0, P_0)}_{\text{plant reconfiguration at fixed prices}} \\ & + \underbrace{y_r(T_1, Z_1, P_1) - y_r(T_1, Z_1, P_0)}_{\text{price effect}}. \end{aligned} \tag{12}$$

The first term measures the direct effect of the productivity shock, holding plant configurations and prices fixed at their baseline levels. The second term captures endogenous reallocation through firms' adjustment of plant locations and production networks, evaluated at fixed prices. The third term isolates the general-equilibrium price response, given the shocked productivity and re-optimized plant configuration.

Table 5 presents the decomposition of sales responses. In regulated regions (NAA), productivity declines are the primary driver of the contraction in sales. Once within-firm substitution is allowed, plant exit and reconfiguration further amplify this decline, while price increases partially offset these effects. In non-regulated regions (AA), sales gains are driven mainly by extensive-margin expansion: new plant entry accounts for roughly 60% of the increase, with price effects explaining most of the remainder.

In the alternative calibration without multi-unit firm linkages, reallocation between NAA

Table 5: Decomposition of Sales Responses

	Total	Productivity	Plant configuration	Prices
Baseline: $\theta = 5.03$, $\Delta T_{\mathbf{NAA}} = -0.035$				
NAA	-0.08	-0.11	-0.03	0.06
		(129%)	(42%)	(-71%)
AA	0.16	0.01	0.09	0.06
		(8%)	(57%)	(35%)
No MU Linkage: $\theta = 3.01$, $\Delta T_{\mathbf{NAA}} = -0.051$				
NAA	-0.07	-0.15	-0.00	0.08
		(205%)	(3%)	(-108%)
AA	0.14	0.00	0.06	0.07
		(0%)	(46%)	(53%)

and AA weakens substantially. The extensive-margin response becomes much smaller, reducing the contribution of plant reconfiguration to overall adjustment. As a result, a larger share of the adjustment occurs through the direct productivity shock and equilibrium price changes. The decomposition shows that omitting multi-unit production networks leads to a fundamentally different interpretation of how the regulation reshapes economic activity across space.

Taken together, the exercises in this section highlight the central role of multi-unit firms in shaping the economic consequences of the regulation. In the baseline model, within-firm substitution amplifies spatial reallocation, strengthens extensive-margin responses, and dampens aggregate price increases. When this channel is attenuated, reallocation across regions weakens, larger productivity shocks are required to match the observed direct effect, and price responses become more pronounced. The decomposition further shows that omitting multi-unit production networks alters not only the magnitude of adjustment, but also the mechanisms through which it occurs—shifting weight away from plant reconfiguration and toward direct productivity losses and price effects. Accounting for multi-unit firms is therefore essential to calculating the aggregate costs of the Clean Air Act, for correctly interpreting the spatial redistribution of activity, and the relative importance of extensive and intensive margin adjustments as well as equilibrium price responses.

7.3 Geographical and Aggregate Pollution and Mortality Outcomes

Given that the regulation led to substantial production spillovers to less regulated parts of the country, an important question is the extent to which the Clean Air Act ultimately improved environmental quality and generated social benefits. Shifting production away from regulated areas reduces emissions locally, but increases emissions elsewhere. The net effect on pollution and health depends on where these production shifts occur, how pollutants are transported through the atmosphere, and where populations are exposed. Answering this question requires going beyond local regulatory impacts and quantifying how changes in production across the entire country translate into changes in pollution concentrations and health damages.

To do this, we combine the model's predicted spatial pattern of production changes with the AP4 pollution-transport model (Muller and Mendelsohn, 2007; Dennin et al., 2024). First, we convert location-level production changes into emissions changes using sector- and pollutant-specific emission-intensity parameters. Because our model relies on estimates of substitution between pollutants and other inputs from Shapiro and Walker (2018), the model's implied changes in emissions incorporate endogenous improvements in pollution intensity. We then feed these emissions changes into AP4, which uses a source–receptor framework to map emissions from each source region into ambient pollution concentrations across all receptor regions. This structure captures both local pollution effects and downwind transport. Finally, we translate changes in pollution concentrations into changes in mortality using standard dose–response functions. We discuss additional details behind these calculations in Appendix F.

Figure 11 shows the model-implied changes in sales. All NAA regions experience sales declines, whereas most attainment (AA) regions exhibit positive leakage effects and increased sales. We then translate these output changes into emissions (Figure 12). Regulated regions display substantial emission reductions, driven both by lower production and by policy-induced declines in emission intensity. Using post-policy emission data, we construct counterfactual pre-policy emission levels and feed both into the AP4 model to obtain pollution concentrations (Figure 13) and associated mortality outcomes (Figure 14) before and after

the policy.

Environmental improvements are widespread across regions. Annual pollution-related deaths per commuting zone decline, on average, from 866 to 851. This 1.7% decline implies that the regulation saved more than 10,500 lives across all commuting zones. However, the magnitude of the gains varies substantially: reductions are modest along the West Coast and considerably larger in the Rust Belt. Figures A9 and A10 help explain this pattern. Figure A9 shows that the West Coast has a relatively small share of PM emissions from the dirty sectors we study, limiting the scope for reductions through this channel. Our framework isolates this mechanism by focusing on policy-induced changes in dirty manufacturing output and emissions, abstracting from other sources of regional pollution. Figure A10 further illustrates dispersion patterns: pollution accumulates more in the East, where flatter terrain and weaker air circulation limit dispersion, whereas stronger winds and higher elevations in the West promote atmospheric mixing and reduce pollution buildup.

7.4 Trading-off Economic Costs and Environmental Benefits

Armed with both changes in economic activity and the lives saved from the reduction in pollution, we now compute the implied value of a statistical life (VSL) that equates the costs and benefits of the regulation. We consider the welfare function $W = RP_0^{-\kappa_0} P_1^{-\kappa_1} D^{-\kappa_2}$, where R is fixed expenditure, P_0 is the price in the regulated sector of the economy, P_1 is the price in the unregulated sector, and D is pollution-related deaths in the regulated sector. We assume $\kappa_0 + \kappa_1 + \kappa_2 = 1$ and that κ_0 and κ_1 measure the importance of these sectors in the economy, such that $\frac{\kappa_0}{\kappa_0+\kappa_1} = s_0$, where s_0 denotes the regulated sector's share of GDP. The coefficient κ_2 captures the cost of deaths from pollution. Using an expenditure-share logic, we posit that $\kappa_2 = \frac{VSL \times D}{GDP}$.

To solve for the implied value of the VSL that equates the costs and benefits of the regulation, we set the change in welfare equal to zero (i.e., $d \ln W = 0$), which yields the following expression:

$$VSL = \frac{GDP}{D} \frac{s_0 d \ln P_0}{s_0 d \ln P_0 - d \ln D},$$

where we assume that prices in the unregulated sector are not affected by the regulation. Thus, given data on GDP, pollution-related deaths D from the AP4 model, and aggregate

changes in output prices and mortality, we obtain a "break-even" VSL that equates the costs and benefits of the regulation.

Using national-level changes in prices $d \ln P_0 = 2.02\%$ and declines in pollution-related mortality $d \ln D = -1.7\%$ we find that a VSL of approximately \$70,000 (in 1970 USD) equalizes economic costs with the reduction in pollution-related mortality.[25] This value is substantially below commonly used benchmarks—for example, \$512,000 in income- and inflation-adjusted terms—implying that the estimated environmental benefits exceed the economic costs under standard VSL assumptions.

Building on the geographic heterogeneity in costs and benefits, we compute a break-even VSL for each region. This calculation incorporates the fact that some regions were more impacted by production distortions, while others experienced larger declines in pollution-related mortality. Figure 15 plots the implied VSL for every commuting zone. There is considerable spatial heterogeneity in the implied break-even VSLs. The West Coast lies at the upper end of the distribution, with values approaching \$151,000, whereas most Rust Belt regions fall below \$70,000. Two forces contribute to this result. First, as shown in Figure 14, pollution-related deaths declined more strongly in the Rust Belt than in the West. In addition, commuting zones in the West experienced larger price increases (Figure 9).

Our model also allows us to explore how leakage within multi-unit firms impacts this break-even VSL. The top panel of Figure 16 plots the aggregate and regional VSLs under our standard model parameterization. As in Section 7.2, we use an alternative parameterization of the model that neutralizes the role of multi-unit firms. The bottom panel plots the implied VSLs under this alternative specification. The substitution parameter θ, which governs the strength of within-firm substitution, has limited effects on environmental outcomes. In contrast, economic responses are more sensitive to θ, leading to noticeable variation in the implied break-even VSLs. When we set $\theta = 3.0$, the aggregate break-even VSL increases to roughly \$90,000. Moreover, this specification accentuates differences between regions with the largest net gains (e.g., the Rust Belt) and those that paid a higher cost per life saved

[25] We use the GDP of the US in 1970 of \$1.073 trillion as well as the share of output from the regulated sector of 3.1%. The calculation also assumes a total number of pollution-related deaths of $D = 722 \times 866$. The absolute magnitude of the break-even VSL also depends on the assumed elasticity of costs with respect to regulation, ϵ. For instance, when we set ϵ equal to 0.1, the aggregate break-even VSL rises to approximately \$165,000.

(e.g., the West).

8 Conclusion

Place-based environmental regulations generate substantial reallocation through both market linkages and within-firm production networks. Using confidential Census data, we provide new evidence on the magnitude and persistence of these leakage effects in the context of the Clean Air Act Amendments. Regulated plants experience large and growing declines in employment and sales, driven in part by plant exit and within-firm reallocation. At the same time, activity expands in unregulated plants within the same firms and in nearby counties. Our results highlight the importance of ownership networks and entry and exit decisions for understanding the full incidence of regulation.

To interpret these empirical findings and quantify aggregate effects, we build a spatial equilibrium model with intra-national trade and multi-plant location choice. The model shows that difference-in-differences estimates overstate the decline in regulated regions because equilibrium adjustments raise activity in unregulated areas. Slightly more than half of the relative employment effect reflects contraction in regulated regions, with the remainder driven by expansion elsewhere. In aggregate, the regulation raises prices by roughly 2% while reducing pollution-related mortality by about 1.7%, saving approximately 10,500 lives.

Combining economic and mortality effects, we recover a break-even value of a statistical life of roughly $70,000 (in 1970 USD), well below commonly used benchmark values, implying that the mortality benefits exceed the economic costs under standard assumptions. However, these effects are highly heterogeneous across space: eastern regions, particularly the Rust Belt, experience larger environmental gains, while benefits along the West Coast are more modest. Because economic adjustment depends critically on the strength of within-firm substitution, accurately measuring substitution along firm networks is essential for assessing both the aggregate cost–benefit trade-off and the geographic distribution of regulatory impacts.

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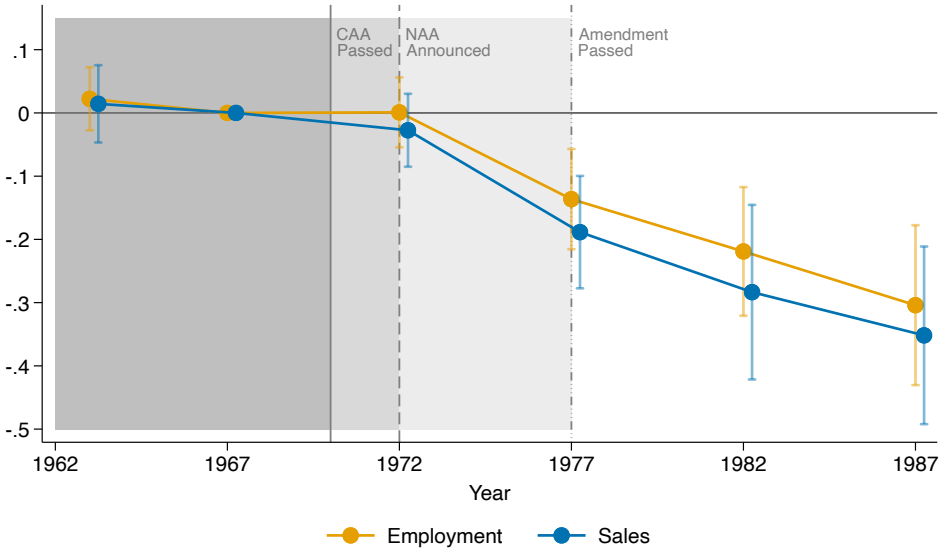
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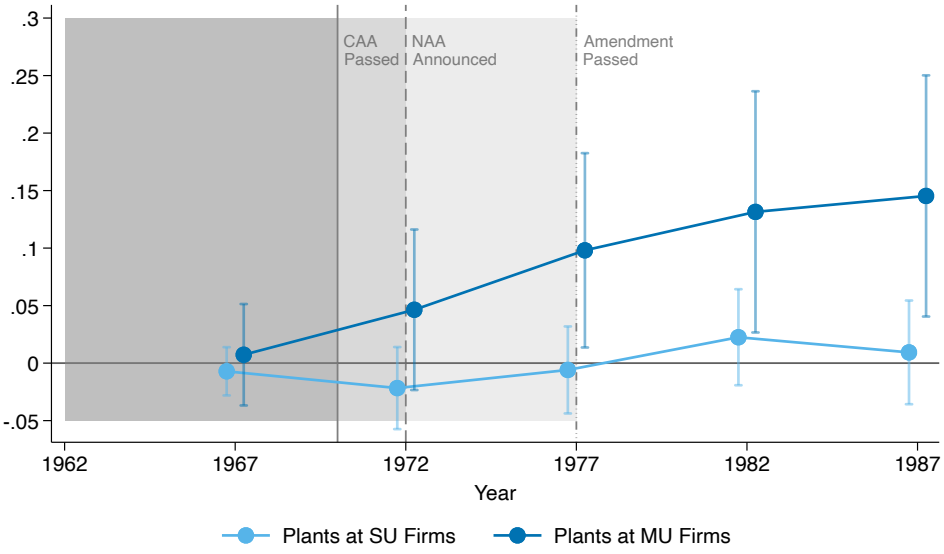
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Figure 1: Direct Effects of Nonattainment on Plant Outcomes



Notes: Figure 1 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on employment and sales. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CM, LBD and EPA Greenbook.

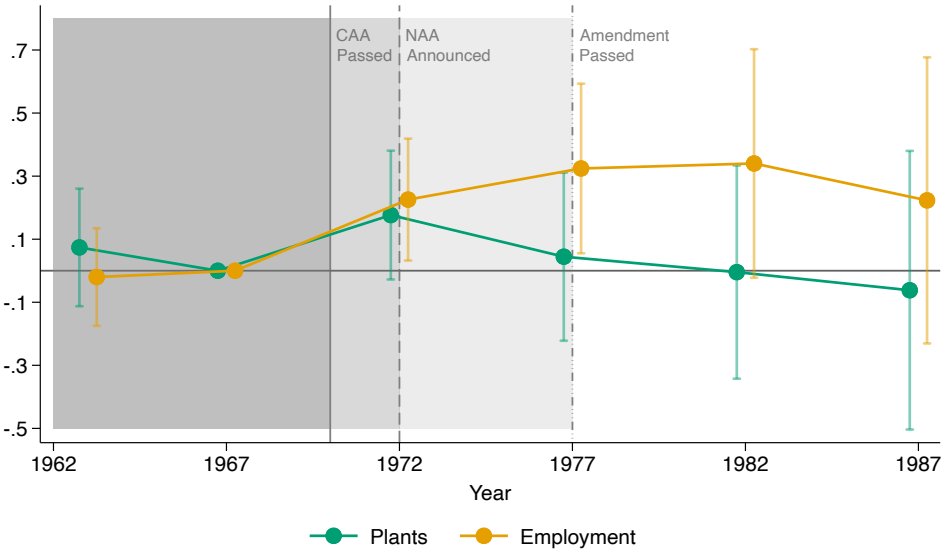
Figure 2: Effect of Nonattainment on Plant Exit



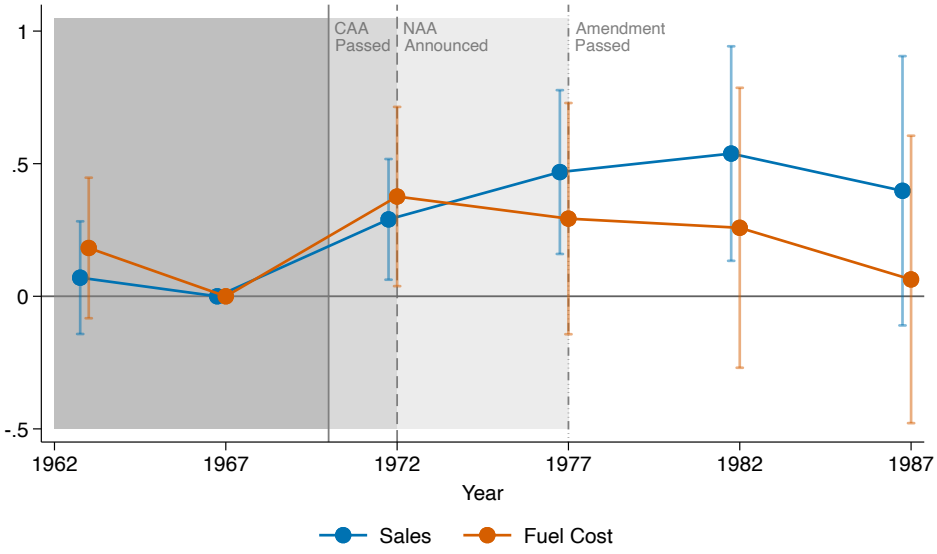
Notes: Figure 2 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on probability of exit. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CM, LBD and EPA Greenbook.

Figure 3: Within Firm leakage Effects

(A) Within Firm leakage: Plants, Employment

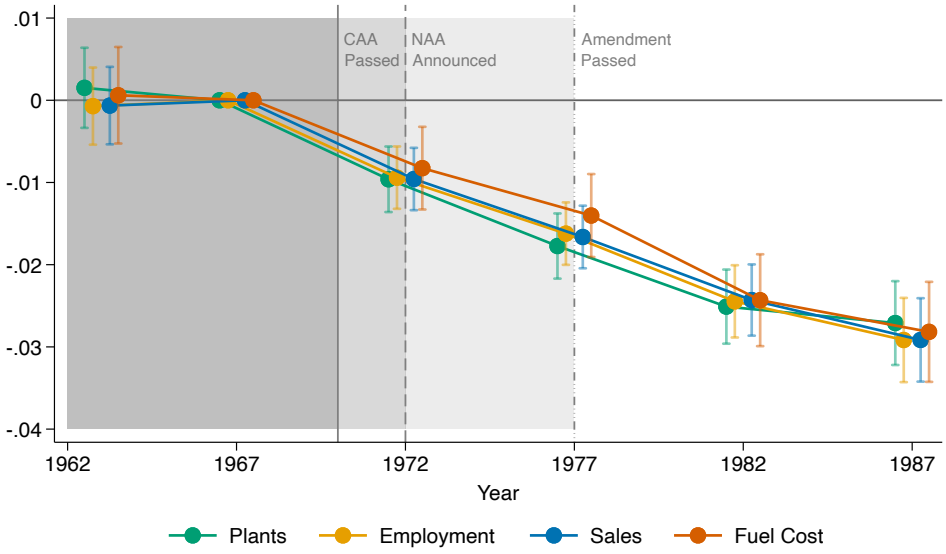


(B) Within Firm leakage: Sales, Fuel Cost



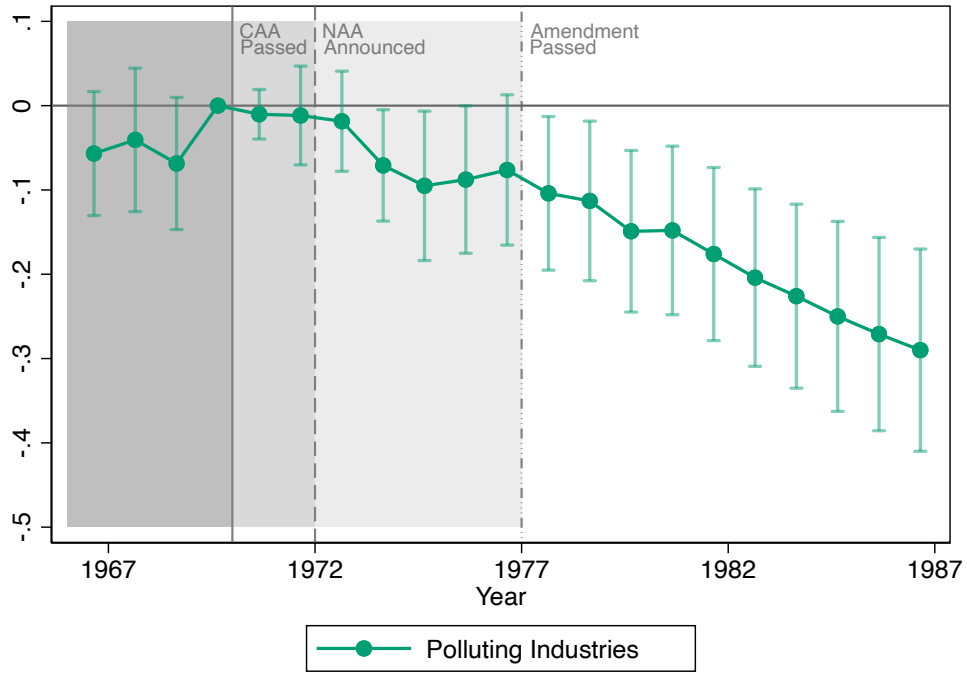
Notes: Figure 3 displays Dynamic DD estimates and 95% confidence intervals describing the within firm leakage effect of the nonattainment standards. Standard errors are clustered at the firm level. Panel (A) displays within firm leakage effects for number of plants and employment while Panel (B), shows leakage of Sales and Fuel Cost. *Source:* Authors' calculations based on CM, LBD and EPA data.

Figure 4: Share of Firm Activity in Nonattainment Counties



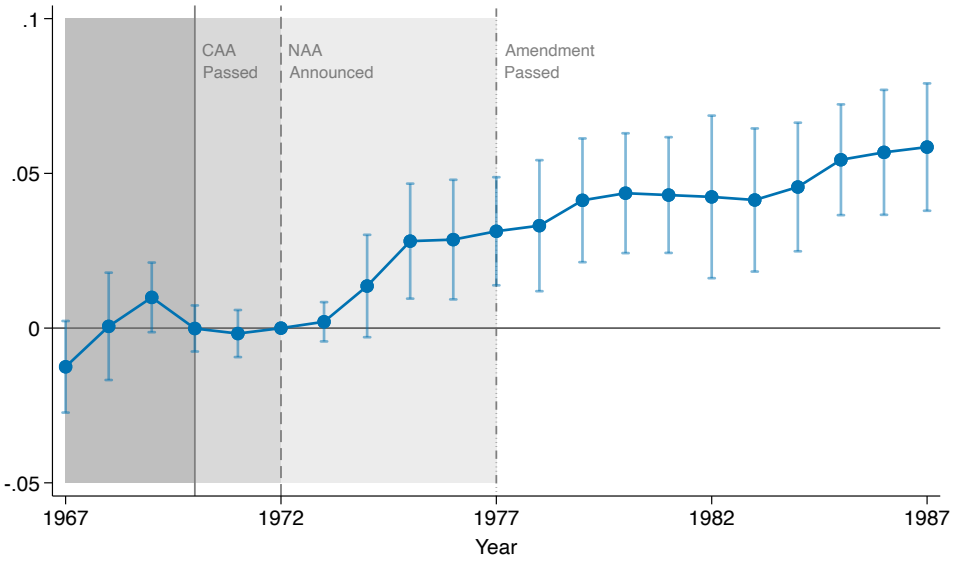
Notes: Figure 4 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on regulated firms' activity share in NAA counties, with standard errors computed using a robust variance estimator. *Source:* Authors' calculations based on CM, LBD and EPA Greenbook.

Figure 5: Direct Effects of Nonattainment on County-Level Employment



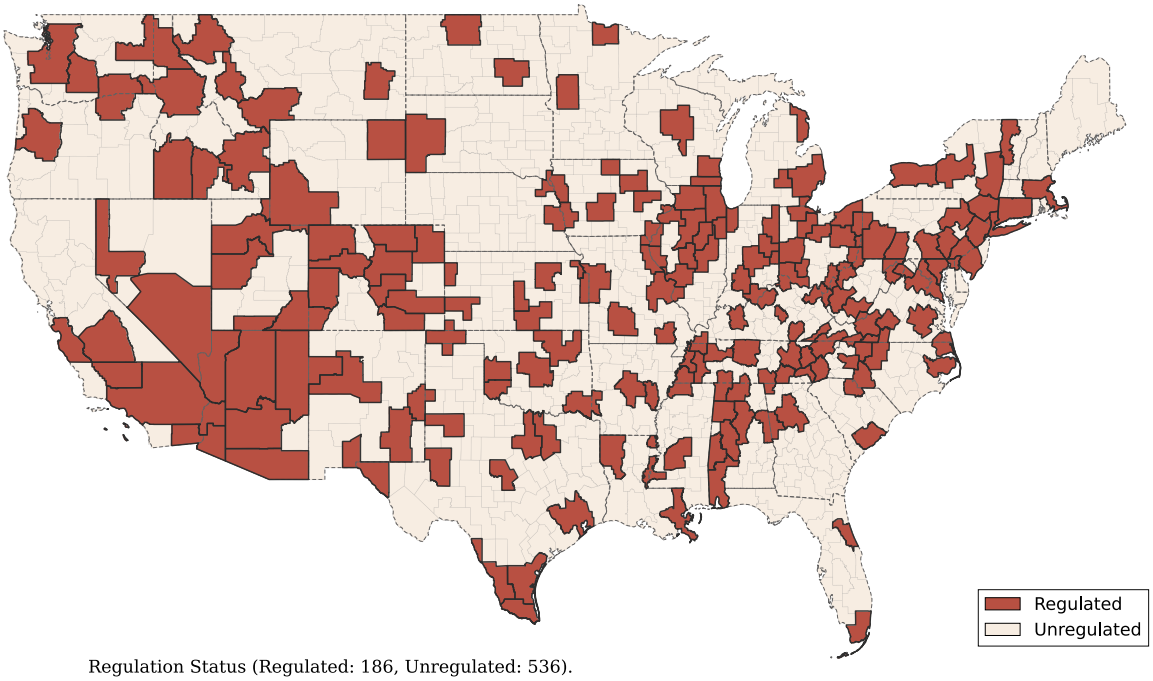
Notes: Figure 5 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on county-level employment. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CBP and EPA Greenbook.

Figure 6: Spatial leakage Effects of Nonattainment



Notes: Figure 6 displays dynamic DD estimates and 95% confidence intervals describing the spatial leakage effect of NAA. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CBP and EPA Greenbook.

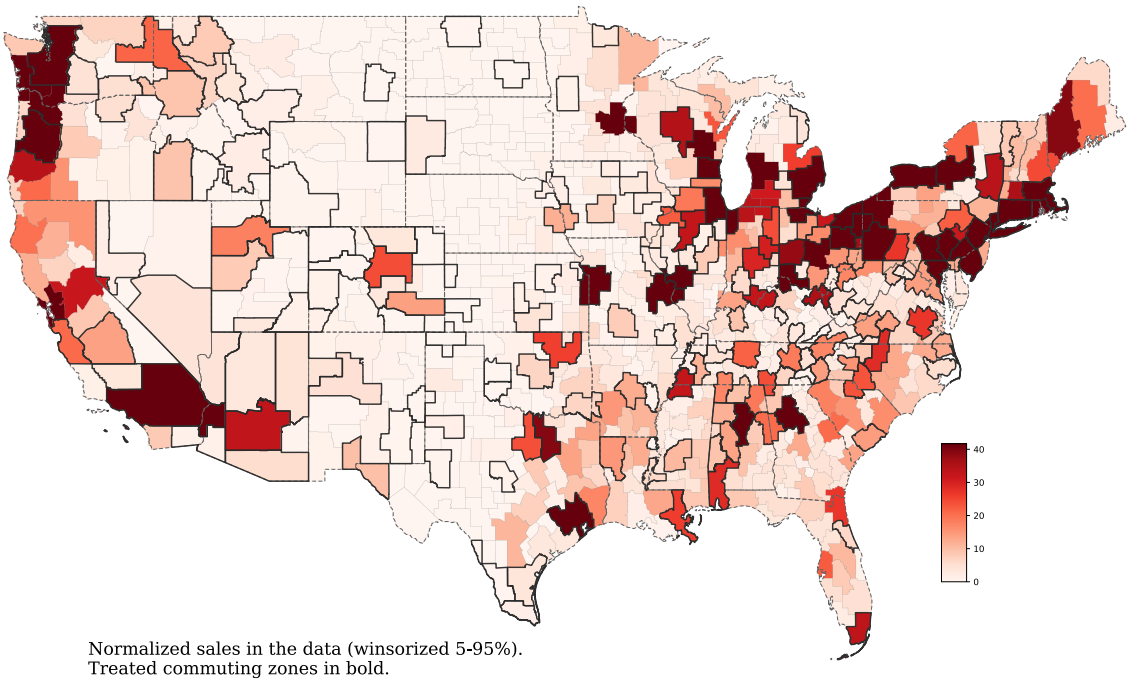
Figure 7: Map of Regulation at the Commuting Zone Level



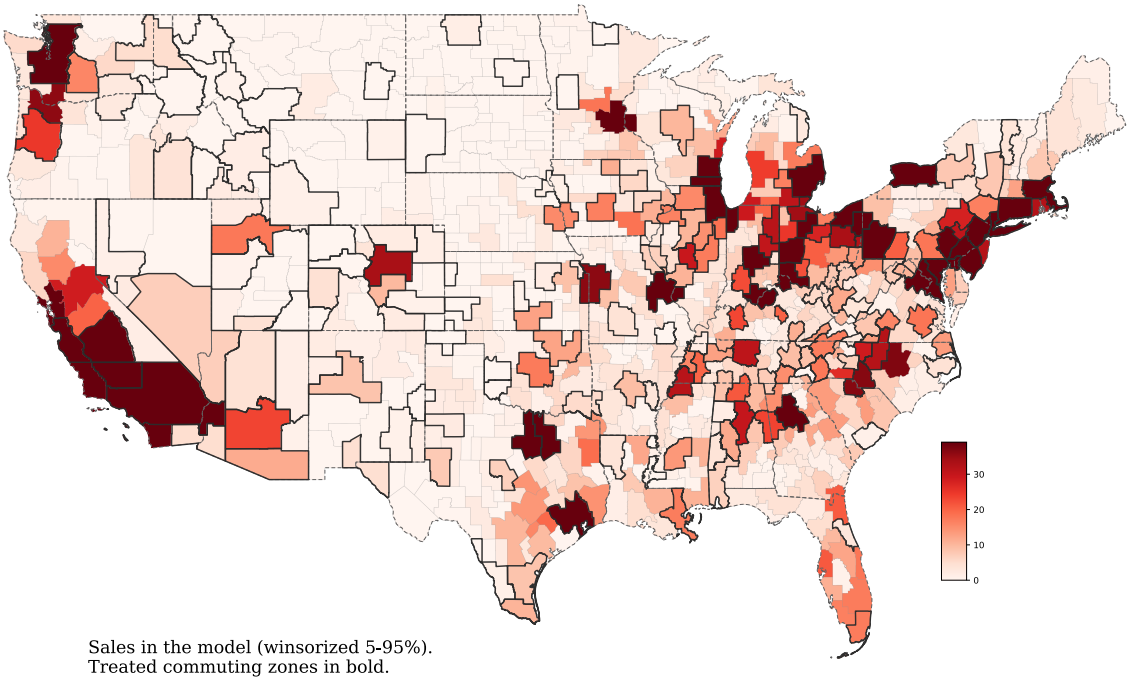
Regulation Status (Regulated: 186, Unregulated: 536).

Notes: Figure 7 displays a map of the regulated and unregulated commuting zones.

Figure 8: Spatial Distribution of Production in Data and Model



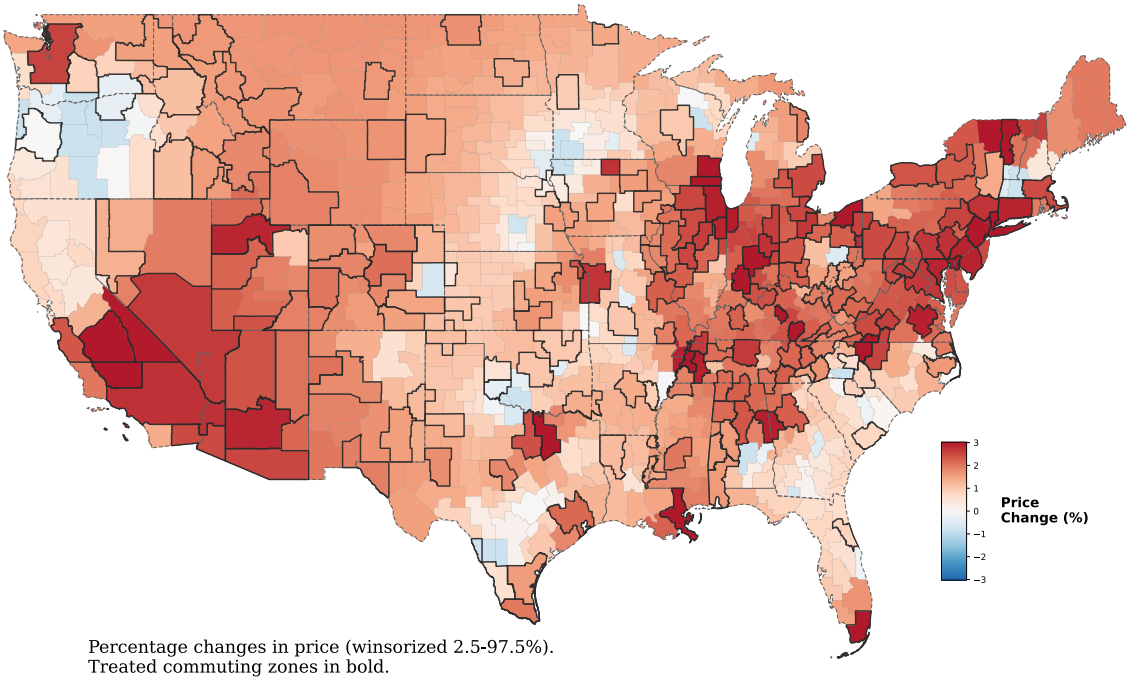
Normalized sales in the data (winsorized 5-95%).
Treated commuting zones in bold.



Sales in the model (winsorized 5-95%).
Treated commuting zones in bold.

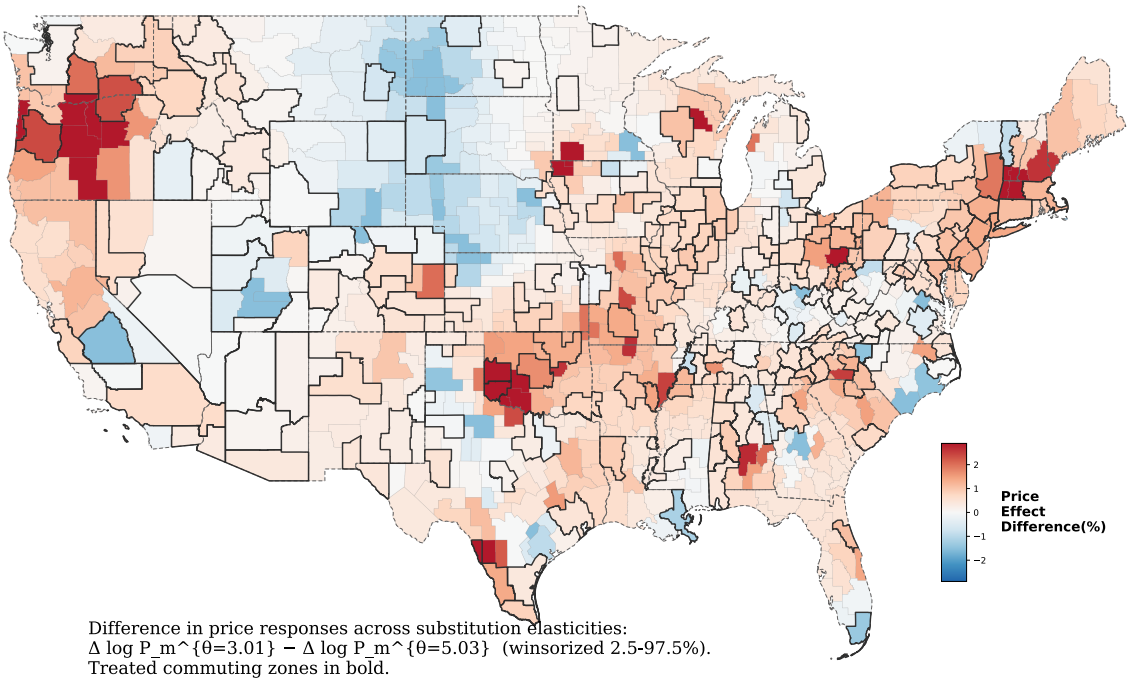
Notes: Figure 8 displays the spatial distribution of production (sales) in data and model. Sales data is constructed using employment data from the CBP and wage data from the IPUMS Census. In the model, sales are proportional to labor costs, which equal employment multiplied by wage. We then normalize the sales so that total sales equal total expenditure across all locations. Expenditure is normalized so that the average expenditure at the commuting zone level equals 10.

Figure 9: Spatial Distribution of Model-Simulated Price Changes



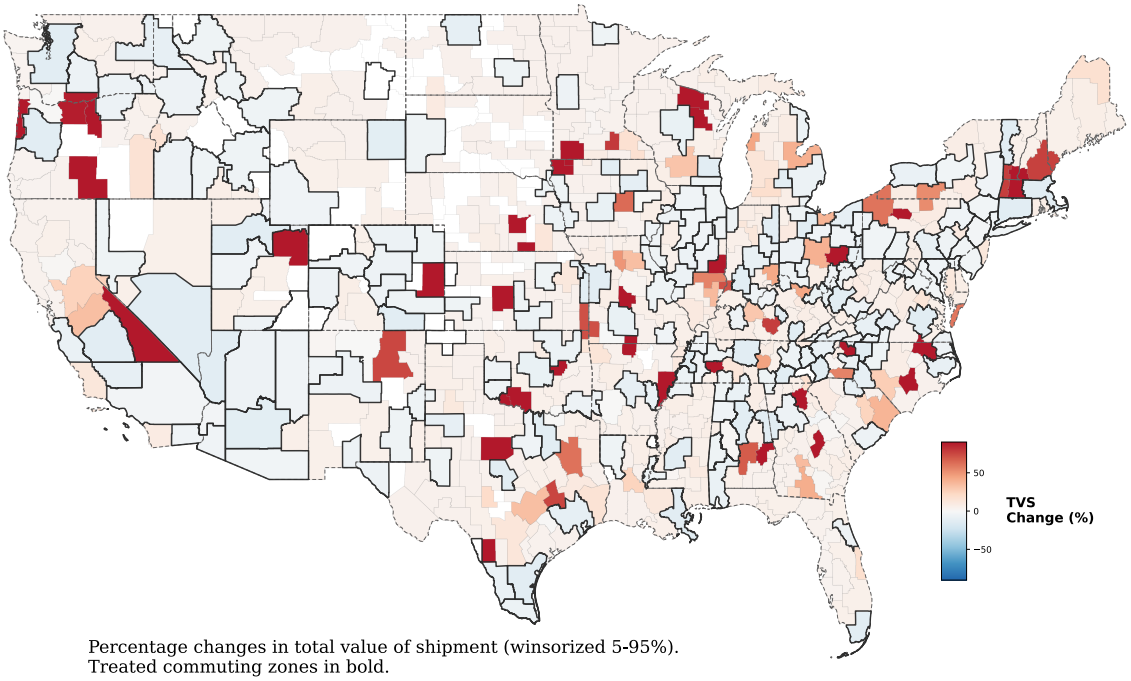
Notes: Figure 9 displays the spatial distribution of percentage price changes as simulated in the model.

Figure 10: Difference in CZ-Level Price Responses Across Within-Firm Substitution Elasticities



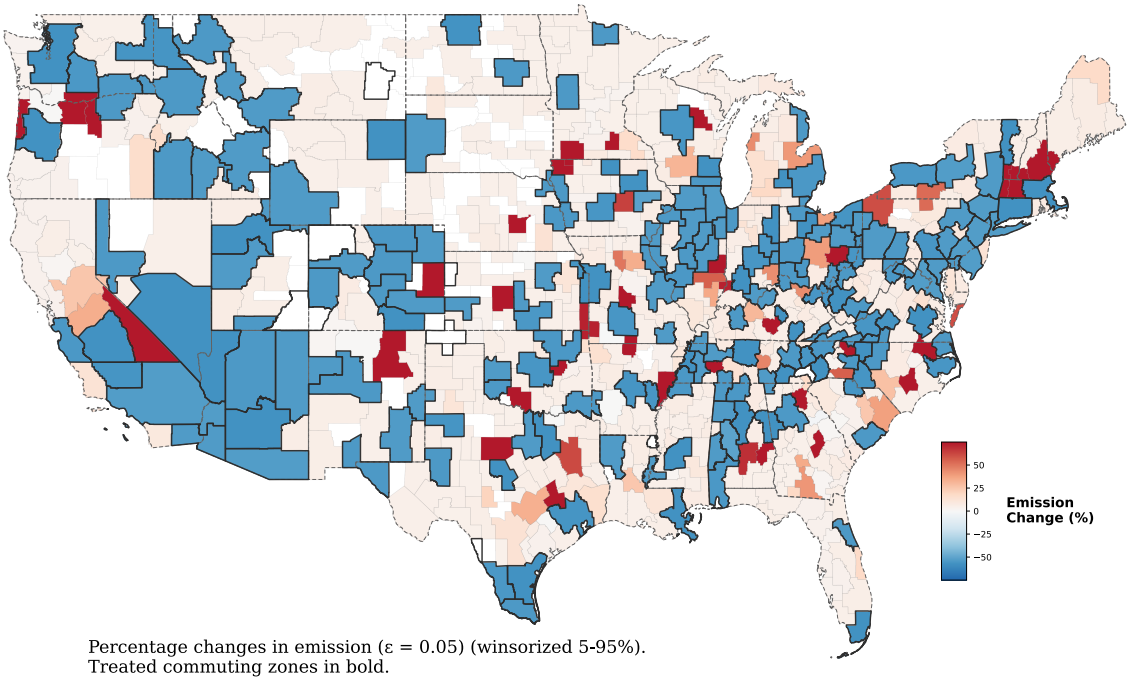
Notes: Figure 10 displays the spatial distribution of differences in percentage log price changes between the low-substitution case ($\theta = 3.01$) and the high-substitution case ($\theta = 5.03$). Positive values indicate larger price increases under lower substitution.

Figure 11: Changes in TVS



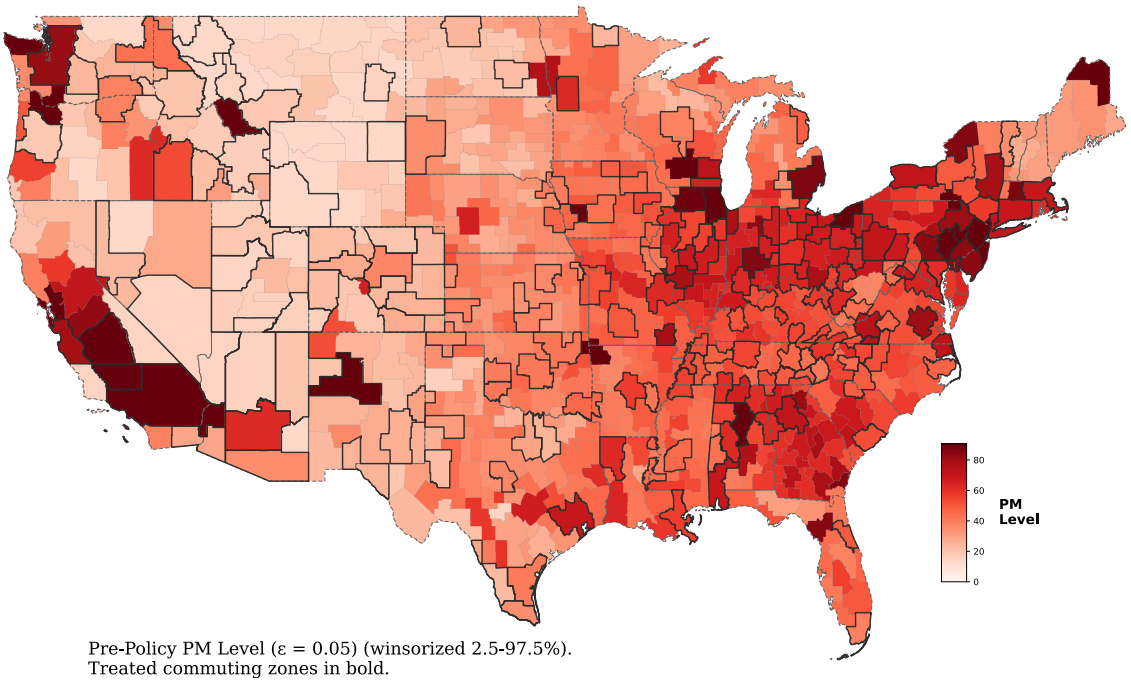
Notes: Figure 11 displays the spatial distribution of percentage TVS changes as simulated in the model.

Figure 12: Changes in Emission

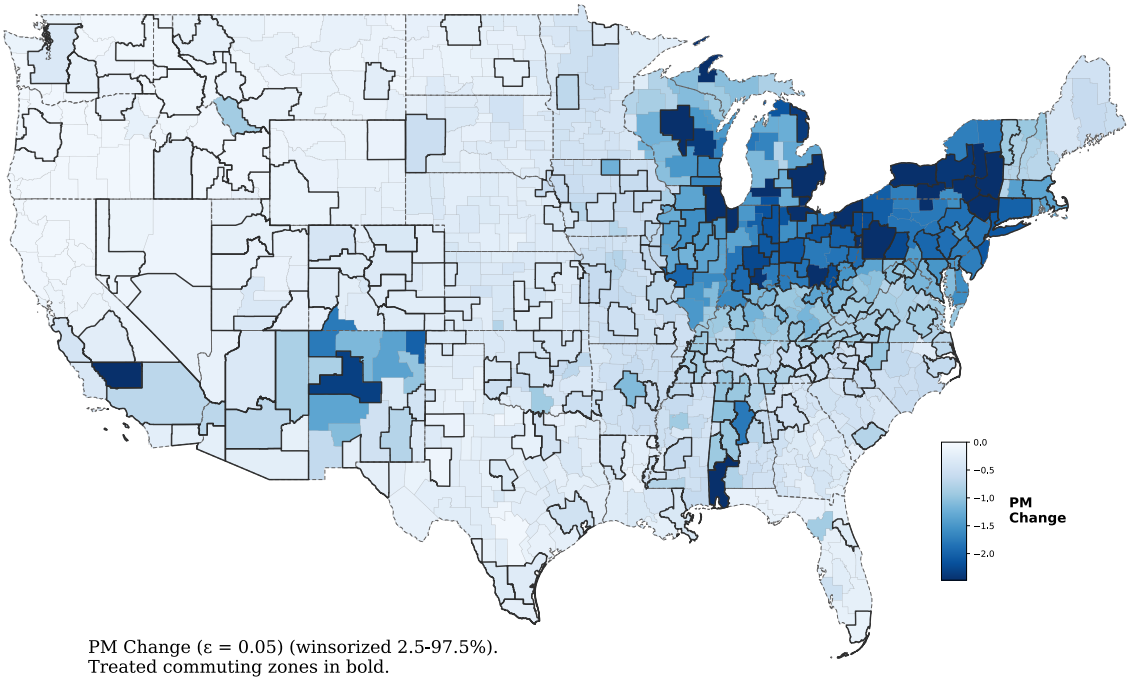


Notes: Figure 12 displays the spatial distribution of percentage emission changes as simulated in the model.

Figure 13: Pre-Policy Pollution Levels and Changes in Pollution



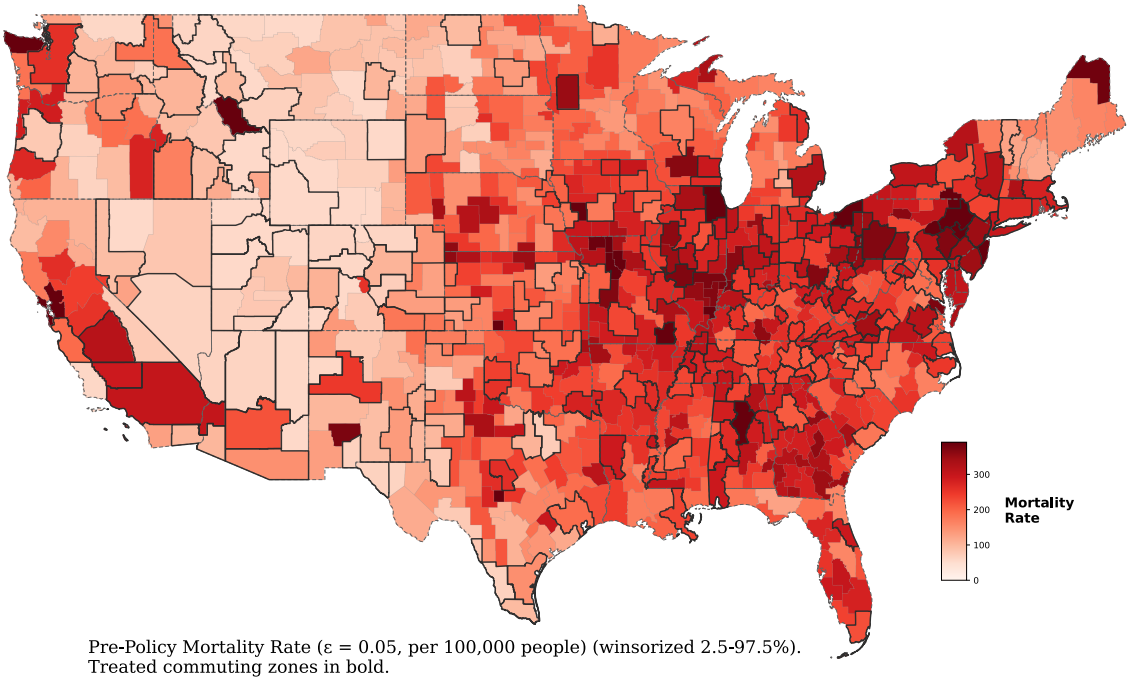
Pre-Policy PM Level (ε = 0.05) (winsorized 2.5-97.5%).
Treated commuting zones in bold.



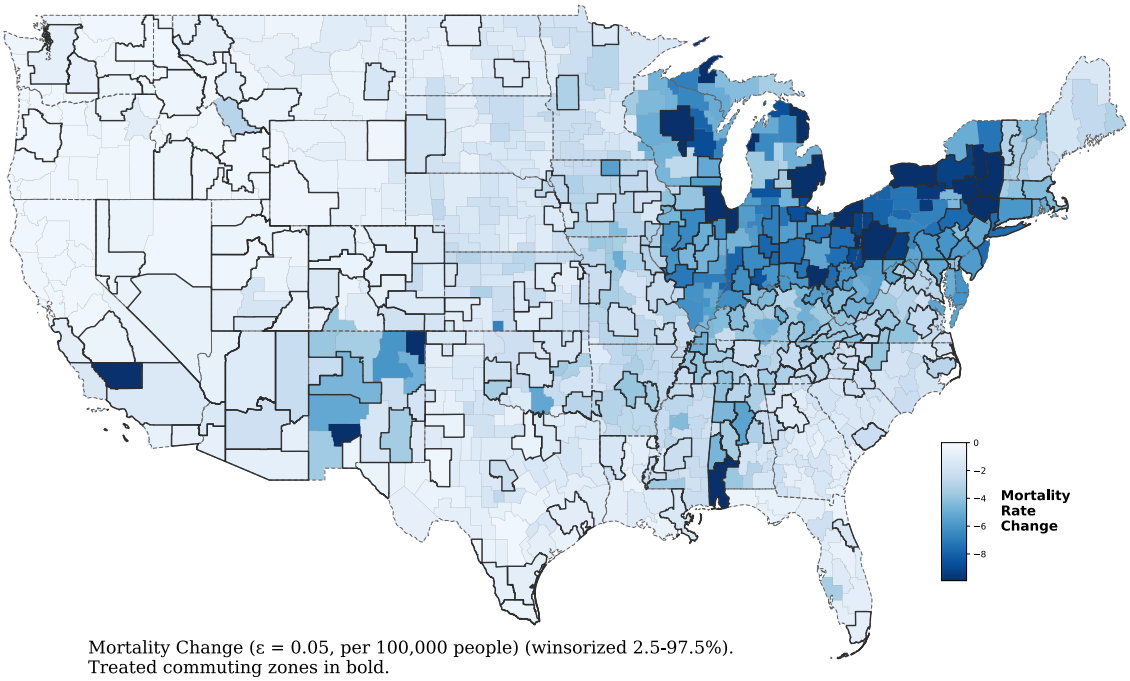
PM Change (ε = 0.05) (winsorized 2.5-97.5%).
Treated commuting zones in bold.

Notes: Figure 13 displays the spatial distribution of pre-policy pollution levels and the policy-induced changes in pollution. Emissions are constructed as observed post-policy emissions adjusted by the model-implied changes in emissions. These emissions are then mapped into ambient pollution concentrations using the AP4 model.

Figure 14: Pre-Policy Mortality Rate and Changes in Mortality Rate



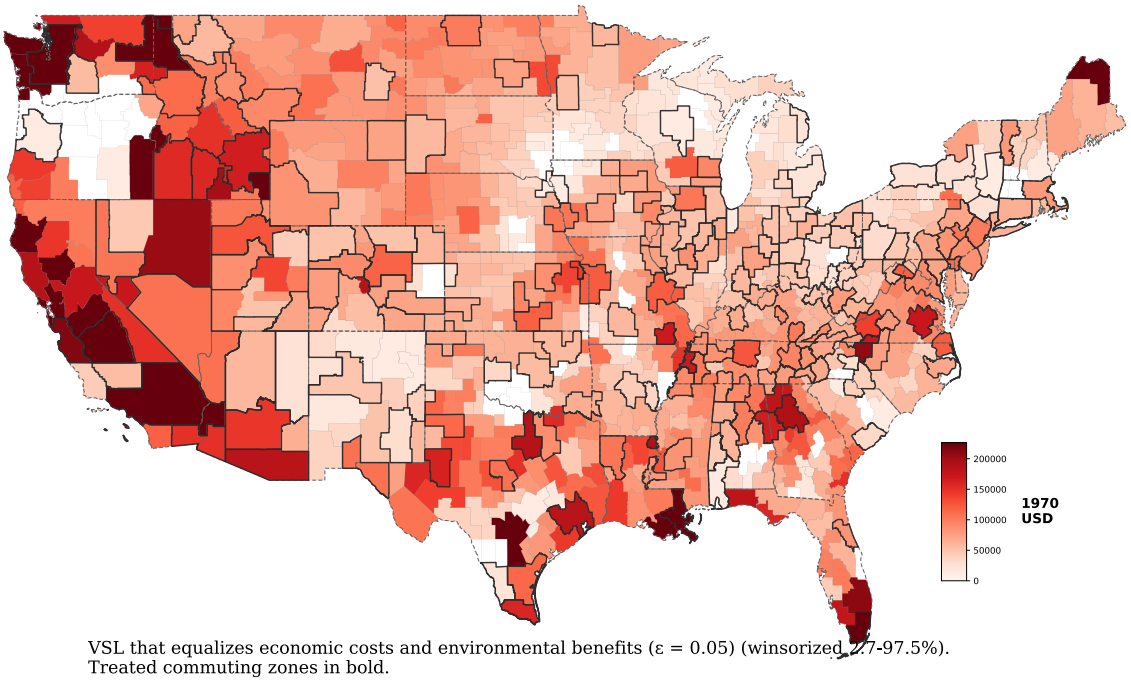
Pre-Policy Mortality Rate (ε = 0.05, per 100,000 people) (winsorized 2.5-97.5%).
Treated commuting zones in bold.



Mortality Change (ε = 0.05, per 100,000 people) (winsorized 2.5-97.5%).
Treated commuting zones in bold.

Notes: Figure 13 displays the spatial distribution of pre-policy pollution-attributable mortality rates and the policy-induced changes in mortality. Mortality rates are obtained by mapping pollution concentrations into health outcomes using the AP4 model.

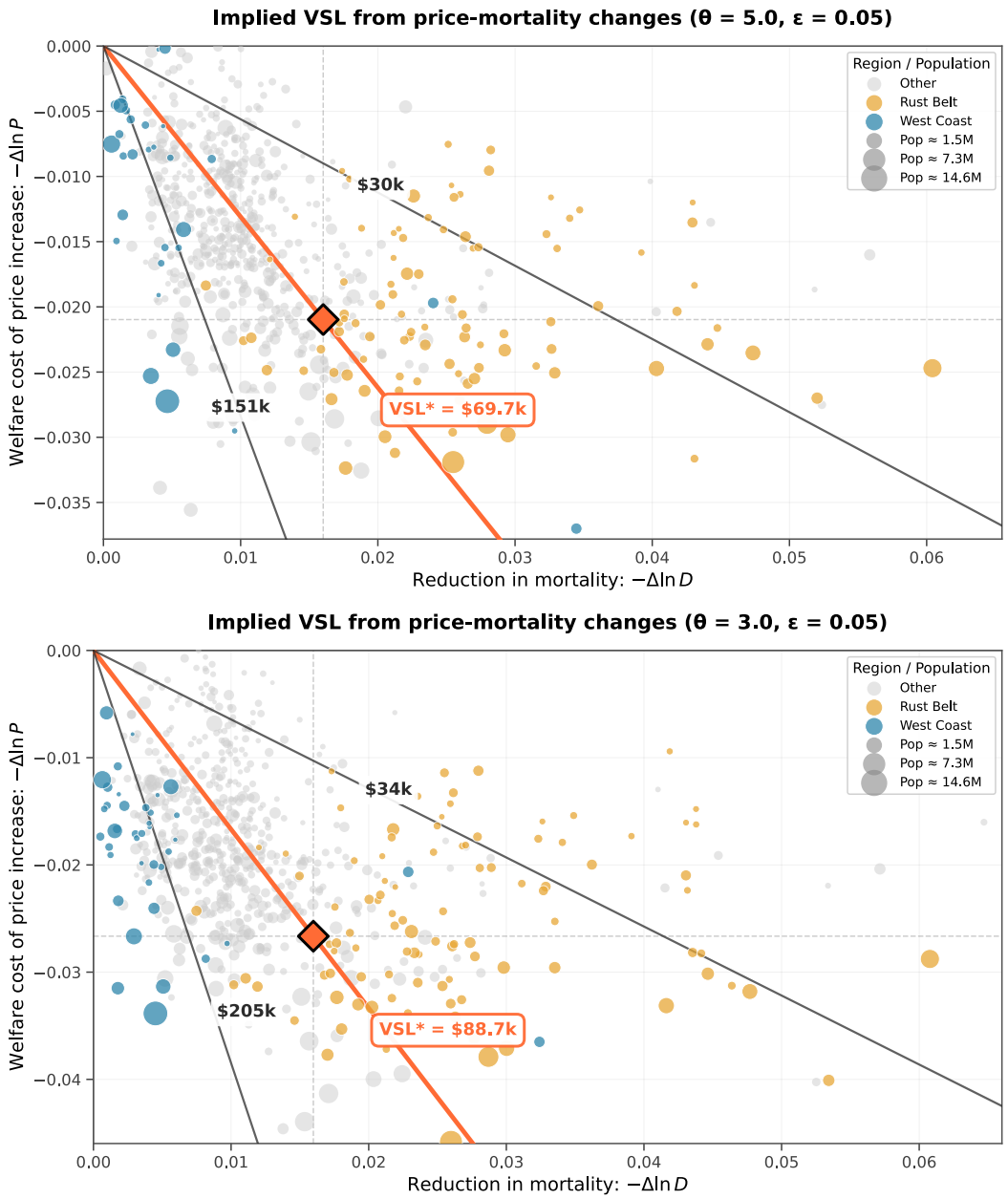
Figure 15: Implied VSL that Equalizes Economic Costs and Environmental Benefits



VSL that equalizes economic costs and environmental benefits (ε = 0.05) (winsorized 2.7-97.5%).
Treated commuting zones in bold.

Notes: This figure plots implied value of statistical life (VSL) that equalizes economic costs and environmental benefits across regions. The sample is restricted to regions experiencing price increases and mortality declines.

Figure 16: Implied Break-Even VSL under Alternative Elasticity Parameter θ



Notes: This figure plots the implied value of a statistical life (VSL) that equalizes welfare losses from price increases and welfare gains from mortality reductions under two alternative values of θ. Each dot represents a location. The black lines correspond to the 10th and 90th percentile constant-VSL schedules across regions. The diamond marks the aggregate point, and the orange line shows the implied break-even VSL at that aggregate. Only regions with rising prices and declining mortality are included.

Online Appendix: Not for Publication

This appendix includes several sections of supplemental information. Appendix A presents definitions of all the variables used in the paper. Appendix B presents additional background details of the CAAA and nonattainment status. Appendix D details the derivation of our motivating two-region model. Appendix G presents figures for additional results. Appendix E explains the implementation of Borusyak and Hull (2023) exposure control.

A Variable Definitions

Variable Name	Description
National Ambient Air Quality Standards (NAAQS)	Identifies Nonattainment Areas (NAA) as counties exceeding NAAQS pollution levels for total suspended particulates.
Exit	Binary indicator for plant activity in year t, equal to 1 if the plant has exited, otherwise equal to 0. *Source:* Census of Manufactures, Longitudinal Business Database.
Xi	Control variables including distance measures and employment for county i's.
Wages	Average manufacturing wages adjusted for demographics and industry affiliation for commuting zone c at time t. *Source:* Census of Manufactures, Longitudinal Business Database.
Labor Productivity	log of total employment divided by total value of shipments *Source:* Census of Manufactures, Longitudinal Business Database.
Energy Efficiency	log of total energy expenditure divided by total value of shipments. *Source:* Census of Manufactures, Longitudinal Business Database.

B CAAA History and Details

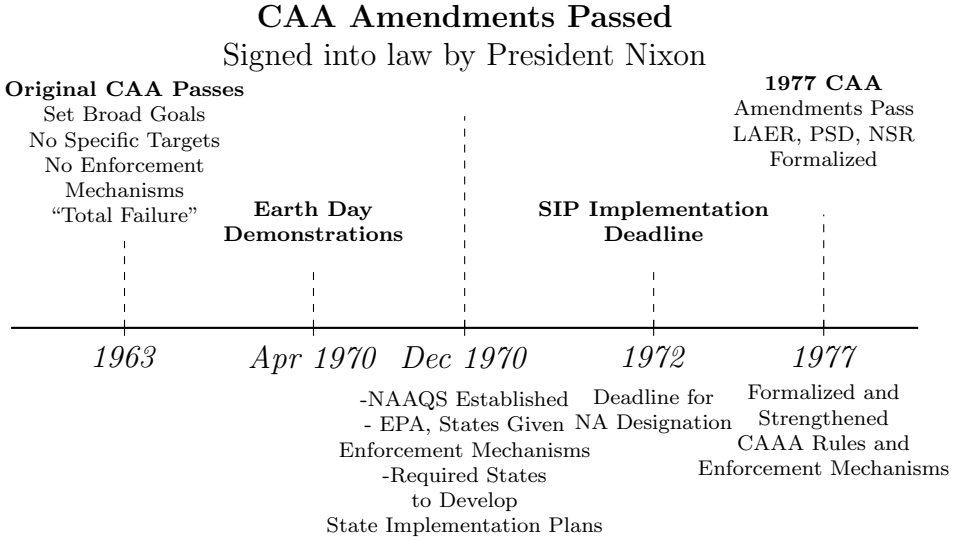
In this appendix we explore the history of the Clean Air Act and provide additional details on its implementation.

Clean Air Act was originally passed in 1963 and the Air Quality Act was passed in 1967. This federal legislation was designed to help develop technologically feasible emission standards. By 1969, these were largely viewed as "nearly a complete failure" Melnick (1983).

Political support for improved federal regulations surged following the well-publisized Cuyahoga river fire and the subsequent Earth Day demonstrations on April 22. This led to President Nixon, despite his anti-regulatory tendencies, drafting the Clean Air Act and the creation of the EPA. Democrats, particularly Senator Edmund Muskie from Maine, had long been pushing for more stringent regulations and played a major role in shaping the final legislation. The Act was passed by the House of Representatives by a vote of 374-1 on June 10, 1970. It passed the Senate 73-0 on September 22, 1970. The senate version was more stringent than the house version and the final bill incorporated much of Senator Muskie's previous written regulation. Muskie and Nixon were political rivals and Muskie accused Nixon of hopping on the environmental bandwagon. The bill was signed into law on December 31, 1970.

As part of the 1970 CAAA, States were required to submit State Implementation Plans (SIPS) by 1972 that would allow them to achieve attainment standards by 1975. EPA had the right to reject SIPS proposed by states. Extensions for achieving these standards were granted for some states until 1977.

In the 1977 amendments to the Clean Air Act, important provisions were introduced to regulate emissions from new stationary sources in both Attainment and Nonattainment areas. Under these amendments, new facilities in Attainment areas were required to incorporate 'best available control technology' to mitigate emissions. In Nonattainment areas, not only were new sources of emissions affected, but also modifications to existing sources. In nonattainment areas, new or modified sources were obligated to achieve the 'lowest available emissions rate' and were further mandated to secure emission offsets to compensate for any additional emissions they generated. Industries varied in how they were required to comply with the LAER. Any plant burning coal in nonattainment area had to achieve percentage reduction of sulfur in fuel. This was commonly done through fuel switching to coal with lower sulfur content. In addition to fuel switching, plants were required to install new abatement capital including scrubbers, electrostatic precipitators and cyclone separators to remove particles from exhaust gases. The 1977 amendments also clarified the enforcement powers of the EPA allowing for civil penalties, non-compliance penalties and construction bans for failure to meet attainment standards. It made noncompliance penalties mandatory



for industrial sources that failed to comply with the regulations.

C AQCR Regulatory Definition

This appendix presents robustness checks using the official Air Quality Control Region (AQCR) designations of nonattainment under the 1970 Clean Air Act Amendments (CAAA). As we describe in the main text, our primary analysis defines nonattainment status at the county level based on monitor data for total suspended particulates (TSP), consistent with the approach taken by Greenstone (2002) and subsequent work. This approach targets areas that likely experienced the most stringent regulation in practice. However, between 1972 and 1977, the Environmental Protection Agency (EPA) implemented nonattainment designations at the AQCR level, not at the county level.

AQCRs were created by EPA in the early 1970s as a mechanism to group counties into airsheds based on atmospheric and geographic characteristics relevant for pollution dispersion. These regions were intended to facilitate coordinated regulatory action across jurisdictions with shared air quality problems. There were 247 AQCRs initially designated, and because some spanned multiple states, the relevant regulatory unit for enforcement became the 313 AQCR-state pairs Murphy (2017). Under the 1970 CAAA, an entire AQCR-state unit was designated nonattainment if any part of it exceeded a pollutant standard, such as the NAAQS for TSP. The designations for these regions were published in the Federal Register and guided state implementation plans (SIPs) in the pre-1977 regulatory framework.

Our preferred approach uses monitor data to assign nonattainment status directly to counties that exceeded the NAAQS threshold for TSP. While this is a reconstruction rather than a contemporaneous regulatory designation, it better captures the locations most likely to face real compliance obligations and enforcement activity. Historical evidence suggests that regulatory effort focused on the most polluted counties, even within larger nonattainment AQCRs (Cropper et al., 2025; Murphy, 2017; Cropper et al., 2023). Thus, while AQCRs served as the legal basis for designation, the binding constraint of the regulation likely operated more granularly.

There are several reasons to prefer the county-level monitor-based measure over the AQCR-based designation. First, even though AQCRs were the formal unit of designation, enforcement was not spatially uniform. In practice, states and local regulators targeted

specific counties with the highest measured pollution levels, suggesting that monitor-based definitions more accurately reflect where regulation actually bound. Second, the AQCR measure is much broader in geographic scope. Over two-thirds of counties fall into nonattainment AQCRs under the 1970 designation, making it difficult to identify an appropriate control group.

Third, evidence from prior studies points to potential anticipation effects and other transitional dynamics that are better aligned with monitor-based definitions than with the AQCR-based legal designations (Sager and Singer, 2025; Clay et al., 2021). Moreover, event study estimates using AQCR definitions exhibit pretrends and less convincing identification (Cropper et al., 2023), while estimates based on monitor-level data better satisfy identification assumptions and align with the timing of regulatory enforcement (Cropper et al., 2025).

To assess robustness to these definitional choices, we estimate two event study specifications. In the first specification, we treat all counties located within nonattainment AQCR-state pairs as treated and compare them to counties in attainment AQCRs. This follows the formal designations issued by EPA between 1972 and 1977. In the second specification, we retain our TSP-based county-level treatment definition but restrict the sample to counties within nonattainment AQCRs. This allows us to assess whether treatment effects are driven by within-AQCR variation.

Figure A7 reports an event study using AQCR-based nonattainment treatment definition. All counties located in a blue region above are defined as treated. As expected, using AQCR to define treatment results in smaller and noisier effects. Using the AQCR measure results in limited within-state regulatory variation. As a result, we report event-studies both with and without state-year fixed effects. Including state-year fixed effects, as we do in our baseline specification in Figure 5, results in imprecise effects given the lack of identifying variation.

Figure A8 examines whether there was a differential response to the nonattainment standards within AQCR regions. To do this, we revert to our monitor based, county-level measure of treatment and the specification used in Figure 5 but remove all attainment AQCR regions. This is comparing monitor counties to counties in "nonattainment" AQCR regions that did not exceed the threshold. Results from Figure A8 are very similar to those in Figure 5 and show that counties we define as regulated based on monitor readings experienced a signifi-

cant decline in employment even relative other counties in their own AQCR. This suggests that regulatory stringency from the nonattainment standards differed significantly within AQCR's.

D Derivations: Two-Region Model

Derivation of Plant Sales Specializing the plant-level revenue formula to the case of two symmetric regions, sales of a single-unit (SU) plant located in j are

$$r_j^{SU} = \left(\Gamma_\theta \frac{\eta}{\eta-1}\right)^{1-\eta} \left(P_j^{\eta-1} + \tau^{1-\eta} P_{j'}^{\eta-1}\right) (\phi T_j)^{\eta-1}.$$

Log-linearizing around the symmetric equilibrium ($T_j = T_{j'}, P_j = P_{j'}$) yields the expression in the main text for $d\ln r_j^{SU}$ and $d\ln l_j^{SU}$.

For a multi-unit (MU) firm, total sales of the plant located in j are obtained by summing over destination markets:

$$r_j^{MU} = \left(\Gamma_\theta \frac{\eta}{\eta-1}\right)^{1-\eta} \phi^{\eta-1} \left(\frac{T_j^\theta}{(T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_j^{\eta-1} + \frac{\tau^{-\theta} T_j^\theta}{(\tau^{-\theta} T_j^\theta + T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_{j'}^{\eta-1} \right).$$

As in Tintelnot (2017), plants set a constant markup $\frac{\eta}{\eta-1}$ over marginal cost, so labor demand and sales remain proportional. Let

$$\omega^{MU} \equiv \frac{1}{1+\tau^{-\theta}} \qquad \text{and} \qquad 1-\omega^{MU} = \frac{\tau^{-\theta}}{1+\tau^{-\theta}}$$

denote the home- and away-market revenue shares of the MU plant in the symmetric equilibrium. Log-linearizing r_j^{MU} around $T_j = T_{j'}$ and $P_j = P_{j'}$ then yields

$$\begin{aligned} d\ln r_j^{MU} &= (\eta-1)\left[\omega^{MU} d\ln P_j + (1-\omega^{MU}) d\ln P_{j'}\right] \\ &\quad + \theta\, d\ln T_j + (\eta-1-\theta)\left[\left(\omega^{MU}\right)^2 + \left(1-\omega^{MU}\right)^2\right] d\ln T_j. \end{aligned}$$

By proportionality of sales and labor demand, the same expression applies to $d\ln l_j^{MU}$.

By symmetry, total sales of the MU plant in j' are

$$r_{j'}^{MU} = \left(\Gamma_\theta \frac{\eta}{\eta-1}\right)^{1-\eta} \phi^{\eta-1} \left(\frac{\tau^{-\theta} T_{j'}^\theta}{(T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_j^{\eta-1} + \frac{T_{j'}^\theta}{(\tau^{-\theta} T_j^\theta + T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_{j'}^{\eta-1} \right),$$

and log-linearization gives

$$\begin{aligned} d\ln r_{j'}^{MU} &= (\eta-1)\left[(1-\omega^{MU}) d\ln P_j + \omega^{MU} d\ln P_{j'}\right] \\ &\quad + (\eta-1-\theta)[2\omega^{MU}(1-\omega^{MU})] d\ln T_j. \end{aligned}$$

Derivation of MU Cutoffs. We assume a fixed mass of active firms, each of which operates at least one plant. Each firm ϕ pays a fixed cost f for opening a second plant. The relevant extensive margin is whether a firm operates one plant (SU) or two plants (MU).

Conditional on operating a single plant in j, standard CES arguments imply SU profits

$$\pi_j^{SU}(\phi) = \phi^{\eta-1}\frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta}\left(P_j^{\eta-1}(c_j^{SU})^{1-\eta} + P_{j'}^{\eta-1}(\tau c_j^{SU})^{1-\eta}\right);$$

A firm operating two plants earns profits

$$\pi^{MU}(\phi) = \phi^{\eta-1}\frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta}\left(P_j^{\eta-1}(c_j^{MU})^{1-\eta} + P_{j'}^{\eta-1}(c_{j'}^{MU})^{1-\eta}\right) - f;$$

Let $\bar{\phi}_j$ denote the productivity of the marginal MU firm headquartered in j, defined by indifference between operating one or two plants:

$$\pi^{MU}(\bar{\phi}_j) = \pi^{SU}(\bar{\phi}_j).$$

Solving for $\bar{\phi}_j$ yields

$$\bar{\phi}_j = \frac{\eta}{\eta-1}(\eta f)^{\frac{1}{\eta-1}}\left(P_j^{\eta-1}\left[(c_j^{MU})^{1-\eta} - (c_j^{SU})^{1-\eta}\right] + P_{j'}^{\eta-1}\left[(c_{j'}^{MU})^{1-\eta} - (\tau c_j^{SU})^{1-\eta}\right]\right)^{\frac{1}{1-\eta}}.$$

Log-linearized MU Cutoffs We now characterize how the MU cutoff responds to changes in productivity and prices in a symmetric equilibrium.

For firms headquartered in j, log-linearizing $\bar{\phi}_j$ around a symmetric equilibrium ($T_j = T_{j'}, P_j = P_{j'}, c_j^{MU} = c_{j'}^{MU}$) yields

$$\begin{aligned} d\ln\bar{\phi}_j = &-\Delta\, d\ln P_j - (1-\Delta)\, d\ln P_{j'} \\ &+ \underbrace{\frac{(1+\tau^{1-\eta}) - (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}}}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - 1 + (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - \tau^{1-\eta}}}_{\theta-(\eta-1)>0\Rightarrow+} d\ln T_j, \end{aligned}$$

while for firms headquartered in j' the corresponding cutoff $\bar{\phi}_{j'}$ satisfies

$$\begin{aligned} d\ln\bar{\phi}_{j'} = &-(1-\Delta) d\ln P_j - \Delta\, d\ln P_{j'} \\ &- \frac{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}}}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - 1 + (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - \tau^{1-\eta}} d\ln T_j, \end{aligned}$$

where

$$\Delta \equiv \frac{(c_j^{MU})^{1-\eta} - (c_j^{SU})^{1-\eta}}{(c_j^{MU})^{1-\eta} - (c_j^{SU})^{1-\eta} + (c_{j'}^{MU})^{1-\eta} - (\tau c_j^{SU})^{1-\eta}} = \frac{\left(1+\tau^{-\theta}\right)^{-\frac{1-\eta}{\theta}} - 1}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - 1 + (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - \tau^{1-\eta}}$$

Adding up these two equations, we can show that

$$d\ln\bar{\phi}_j + d\ln\bar{\phi}_{j'} = -(d\ln P_j + d\ln P_{j'}) - d\ln T_j$$

Price Index We have the price index defined as

$$\begin{aligned} P_j^{1-\eta} = &\int_0^{\bar{\phi}_j} p_j^{SU}(\phi)^{1-\eta}\, dG_j(\phi) + \int_{\bar{\phi}_j}^{\infty} p_j^{MU}(\phi)^{1-\eta}\, dG_j(\phi) \\ &+ \tau^{1-\eta}\int_0^{\bar{\phi}_{j'}} p_{j'}^{SU}(\phi)^{1-\eta}\, dG_{j'}(\phi) + \int_{\bar{\phi}_{j'}}^{\infty} p_{j'}^{MU}(\phi)^{1-\eta}\, dG_{j'}(\phi). \end{aligned}$$

Around the symmetric equilibrium, the log-linearized price index is

$$\begin{aligned} d\ln P_j = &-\underbrace{\left(\frac{\int^{\bar{\phi}_j} p_j^{SU}(\phi)^{1-\eta} dG_j}{P_j^{1-\eta}} + \left[\frac{\int_{\bar{\phi}_j}^{\infty} p_j^{MU}(\phi)^{1-\eta} dG_j}{P_j^{1-\eta}} + \frac{\int_{\bar{\phi}_{j'}}^{\infty} p_{j'}^{MU}(\phi)^{1-\eta} dG_{j'}}{P_j^{1-\eta}}\right]\omega^{MU}\right)}_{S_D} d\ln T_j \\ &- \frac{p_j^{MU}(\bar{\phi}_j)^{1-\eta}}{(1-\eta)P_j^{1-\eta}}(d\bar{\phi}_j + d\bar{\phi}_{j'}) + \frac{p_j^{SU}(\bar{\phi}_j)^{1-\eta}}{(1-\eta)P_j^{1-\eta}}(d\bar{\phi}_j + \tau^{1-\eta} d\bar{\phi}_{j'}) \end{aligned}$$

where we define S_D as the share of sales to market j from all the plants located in j. We collect terms since $p_j(\bar{\phi}_j) = p_{j'}(\bar{\phi}_{j'})$ in the initial equilibrium. Similarly, we can log-linearize price index $P_{j'}$ as

$$\begin{aligned} d\ln P_{j'} = &-(1-S_D) d\ln T_j \\ &- \frac{p_j^{MU}(\bar{\phi}_j)^{1-\eta}}{(1-\eta)P_j^{1-\eta}}(d\bar{\phi}_j + d\bar{\phi}_{j'}) + \frac{p_j^{SU}(\bar{\phi}_j)^{1-\eta}}{(1-\eta)P_j^{1-\eta}}(\tau^{1-\eta} d\bar{\phi}_j + d\bar{\phi}_{j'}) \end{aligned}$$

Again add up these two equations we have

$$d\ln P_j + d\ln P_{j'} = -d\ln T_j + (d\ln\bar{\phi}_j + d\ln\bar{\phi}_{j'}) \underbrace{\frac{\bar{\phi}_j\left[p^{SU}(\bar{\phi}_j)^{1-\eta}(1+\tau^{1-\eta}) - 2p^{MU}(\bar{\phi}_j)^{1-\eta}\right]}{P_j^{1-\eta}(1-\eta)}}_{C}$$

It is then straight-forward to see, combined with the fact that $d\ln\bar{\phi}_j + d\ln\bar{\phi}_{j'} = -(d\ln P_j + d\ln P_{j'}) - d\ln T_j$, we have

$$d\ln P_j + d\ln P_{j'} = -d\ln T_j \quad d\ln\bar{\phi}_j + d\ln\bar{\phi}_{j'} = 0$$

Comparative Statics We now substitute this relationship $d\ln P_{j'} = -d\ln T_j - d\ln P_j$ back to $d\ln\bar{\phi}_j$ and obtain

$$d\ln\bar{\phi}_j = -\Delta d\ln P_j - (1-\Delta)(-d\ln P_j - d\ln T_j) + \frac{(1+\tau^{1-\eta}) - (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}}}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - 1 + (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - \tau^{1-\eta}} d\ln T_j$$
$$= (1-2\Delta)d\ln P_j + \underbrace{\frac{1}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - 1 + (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - \tau^{1-\eta}}}_{\tilde{\gamma}} d\ln T_j$$

While

$$d\ln\bar{\phi}_{j'} = -(1-2\Delta)d\ln P_j - \tilde{\gamma}d\ln T_j$$

It is also useful to note that $1-2\Delta = (1-\tau^{1-\eta})\tilde{\gamma}$.

We can show $d\ln P_j$ can be simplified to

$$d\ln P_j = -S_D d\ln T_j + \underbrace{\frac{\bar{\phi}_j p_j^{SU}(\bar{\phi}_j)^{1-\eta}}{(1-\eta)P_j^{1-\eta}}(1-\tau^{1-\eta})}_{\alpha(\bar{\phi})} d\ln\bar{\phi}_j = -S_D d\ln T_j + \alpha(\bar{\phi})[(1-2\Delta)d\ln P_j + \tilde{\gamma}d\ln T_j]$$

$$\Rightarrow d\ln P_j = -\frac{S_D - \alpha(\bar{\phi})\tilde{\gamma}}{1-\alpha(\bar{\phi})(1-2\Delta)} d\ln T_j = -\underbrace{\frac{S_D - \alpha(\bar{\phi})\tilde{\gamma}}{1-\alpha(\bar{\phi})(1-\tau^{1-\eta})\tilde{\gamma}}}_{\Lambda} d\ln T_j$$

Since $0 < S_D < 1$, $\alpha(\bar{\phi}) < 0$, it is easy to show that $\Lambda > 0$, i.e., $d\ln P_j > 0$ when $d\ln T_j < 0$. In addition, since

$$d\ln\bar{\phi}_j = [(1-\tau^{1-\eta})\Lambda - 1]\tilde{\gamma}d\ln T_j$$

we can also show $d\ln\bar{\phi}_j < 0$ if $(1-\tau^{1-\eta})\Lambda < 1$. The later is true since $S_D(1-\tau^{1-\eta}) < 1$.

Finally, $d\ln P_{j'} = -(1-\Lambda)d\ln T_j$. When τ is large enough, we have $\Lambda < 1$ and $d\ln P_{j'} > 0$ too when $d\ln T_j < 0$.

Aggregate Labor Demand In a symmetric equilibrium, labor demand in j comes from SU firms in location j as well as plants of domestic and foreign MU firms. Write these as

$$L_j = \left(\int^{\bar{\phi}_j} l(\phi) dG_j + \int_{\bar{\phi}_j} l(\phi) dG_j + \int_{\bar{\phi}_{j'}} l(\phi) dG_{j'} \right)$$

Letting α_{SU} be the share of labor demand in region j coming from single unit firms, we can log-linearize this (with symmetry) as

$$
\begin{aligned}
d\ln L_j = & \underbrace{(\eta-1)d\ln T_j}_{\text{Direct Effect¡0}} \\
& + \underbrace{(\eta-1)\left[\alpha^{SU}(\omega^{SU}d\ln P_j + (1-\omega^{SU})d\ln P_{j'}) + (1-\alpha^{SU})(\omega^{MU}d\ln P_j + (1-\omega^{MU})d\ln P_{j'}\right]}_{\text{Product Market leakage>0}} \\
& \underbrace{+\frac{g(\bar{\phi}_j)}{L_j}l(\bar{\phi}_j)^{SU}d\bar{\phi}_j}_{\text{Relocation<0}}
\end{aligned}
$$

where α^{SU} is the share of domestic labor demand coming from single unit firms and $\omega^{MU} = \frac{1}{1+\tau^{-\theta}}$ is the share of MU revenue stemming from sales to j. The last line uses $d\bar{\phi}_j = -d\ln\bar{\phi}_{j'}$ and $l(\bar{\phi}_j)^{MU} = l(\bar{\phi}_{j'})^{MU}$. Similarly we can log-linearize the labor demand for j'

$$
\begin{aligned}
d\ln L'_j = & \underbrace{(1-\alpha^{SU})(1-\omega^{MU})(\eta-1-\theta)d\ln T_j}_{\text{Intrafirm Leakage Effect>0}} \\
& + \underbrace{(\eta-1)\left[\alpha^{SU}((1-\omega^{SU})d\ln P_j + \omega_{SU}d\ln P_{j'}) + (1-\alpha^{SU})((1-\omega_{MU})d\ln P_j + \omega^{MU}d\ln P_{j'}\right]}_{\text{Product Market leakage>0}} \\
& \underbrace{+\frac{g(\bar{\phi}_{j'})}{L'_j}l(\bar{\phi}_{j'})^{SU}d\bar{\phi}_{j'}}_{\text{Relocation>0}}
\end{aligned}
$$

Since employment in j' goes up unambiguously, the DiD estimator $|d\ln L_j - d\ln L_{j'}|$ overstates the equilibrium aggregate effect of regulation.

E Borusyak and Hull (2023) Exposure Control

We construct counterfactual exposure measures at the firm- and county-level. We proceed as follows:

1. In the sample of monitored counties, estimate linear probability model

$$treat_c = \beta_0 + \beta_1 \log(pop)_c + \beta_2 \log(\text{total emp})_c + \epsilon_c$$

2. Obtain $\{x_c'\hat{\beta}, \hat{\epsilon}_c\}_c$ and let N_c be the number of regulated counties

3. Counterfactual regulation: Compute score $= x_c'\hat{\beta} + \hat{\epsilon}_{c' \neq c}$ and consider N_c counties with largest score as (pseudo)-regulated

4. Compute IE_{cj}^{Pseudo} and $treat_f^{Pseudo}$ based on counterfactual regulation measure

5. Take average across 500 permutations of $\hat{\epsilon}_c$

6. Add as control variable to specifications (3)

F Pollution Transportation Model Implementation

We use the latest version of the Air Pollution Emission Experiments and Policy analysis (APEEP) model, AP4, to translate changes in emissions implied by our model into ambient pollution concentrations and associated mortality risk (Dennin et al., 2024).

Production at location l for producer ω is given by

$$y_l(\omega) = \phi_l(\omega)\,\bar{T}_l\,e(\omega)^{\epsilon}\,l(\omega)^{1-\epsilon},$$

where $e(\omega)$ denotes emissions input, $l(\omega)$ denotes labor input, and $\bar{T}_l$ captures location-specific technology.

Cost minimization implies emissions demand

$$e_l = \frac{\eta - 1}{\eta}\,\epsilon\,\frac{P_l Y_l}{r_l},$$

where r_l is the emissions price, P_l is the output price index, and Y_l is total output at location l.

The implied unit cost function is

$$c_l(\omega) = \frac{\bar{w}_l^{1-\epsilon} r_l^{\epsilon}}{\phi_l(\omega)\bar{T}_l} = \frac{w_l}{\phi_l(\omega) T_l},$$

where $T_l \equiv \bar{T}_l / r_l^{\epsilon}$. From estimation, we recover changes in effective technology as

$$\hat{T}_l \equiv \frac{T_l'}{T_l} = \left(\frac{r_l'}{r_l}\right)^{-\epsilon},$$

or equivalently $1 - dT_l = \hat{T}_l$.

Changes in emissions follow as

$$\hat{e}_l \equiv \frac{e_l'}{e_l} = \frac{P_l' Y_l'}{P_l Y_l} \Big/ \frac{r_l'}{r_l} = \frac{P_l' Y_l'}{P_l Y_l} \Big/ \hat{T}_l^{-1/\epsilon}.$$

These changes are computed at the plant level and aggregated to the location level.

AP4 Calibration and Counterfactual Construction. The AP4 model maps emissions to ambient pollution using Source-Receptor (SR) matrices, which describe how emissions originating from a given county or point source affect pollution concentrations in all counties.

These matrices incorporate atmospheric transport mechanisms such as wind speed, wind direction, and emission height. We take the relative weights in the SR matrices as given.

Because comprehensive emissions and pollution data are not available prior to 1990, we calibrate a scale parameter using observed pollution data in 1990. After calibration, we input observed 1990 emissions into the model to compute implied pollution levels for all counties. This step is necessary because observed pollution data in 1990 cover fewer than 1,000 counties. The AP4 model also provides location-specific mortality rates attributable to pollution exposure.

To construct pre-regulation pollution levels, we infer emissions in 1970 using model-implied emission changes:

$$e_l^{1970} = \frac{e_l^{1990}}{\hat{e}_l}.$$

Since our structural model focuses on pollution-intensive industries, we assume emissions from other sources remain unchanged. Total emissions in 1970 are therefore constructed as

$$e_l^{1970} = e_l^{1990} - e_l^{1990,\text{dirty}} + \frac{e_l^{1990,\text{dirty}}}{\hat{e}_l}.$$

These emissions are then fed into the calibrated AP4 model to compute counterfactual pollution concentrations and mortality rates, which we compare to post-regulation outcomes.

Emission Source Classification. The AP4 model distinguishes three emission source types based on discharge height: ground-level sources (e.g., vehicle exhaust and open burning), non-EGU point sources associated with industrial manufacturing, and EGU point sources associated with electricity generation. The SR matrices for EGU sources are defined at the plant level rather than the county level.

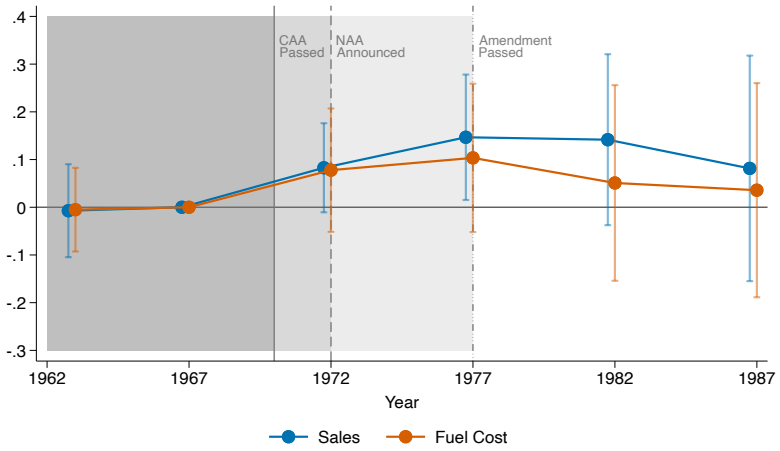
In historical data prior to 1990, emissions are not separately reported for EGU and non-EGU sources. We therefore combine these sources and apply the non-EGU SR matrix. Since our analysis focuses on policy-driven changes in industrial pollution, this approximation should have limited impact unless it substantially alters baseline pollution levels.

G Appendix Figures

Figure A1: Within Firm leakage Effects: Discrete Exposure Variable

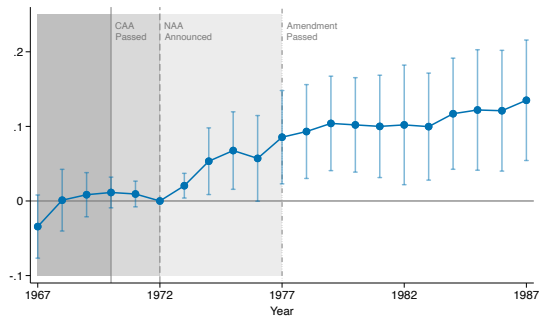


(A) Employment and Number of Plants

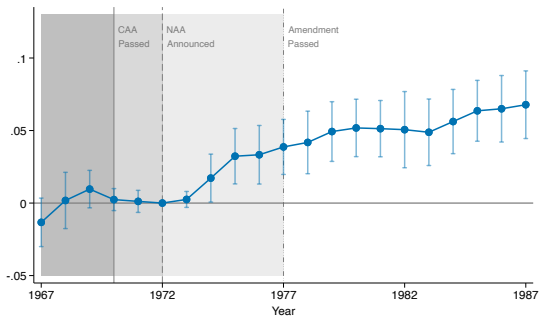


(B) Sales and Cost of Fuels

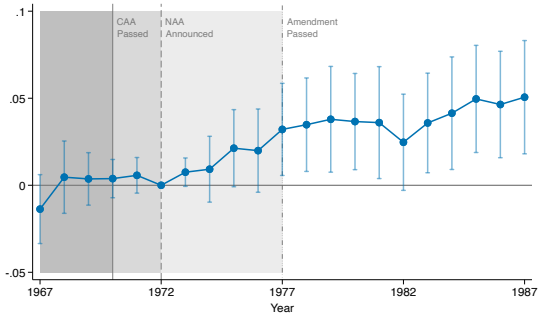
Figure A2: Spatial leakage: Robustness



(A) Spatial leakage: $\delta = 1$



(B) Spatial leakage: $\delta = 3$



(C) Spatial leakage: Regulated Employment Within 40 Miles

Figure A3: Effects of Nonattainment across Manufacturing

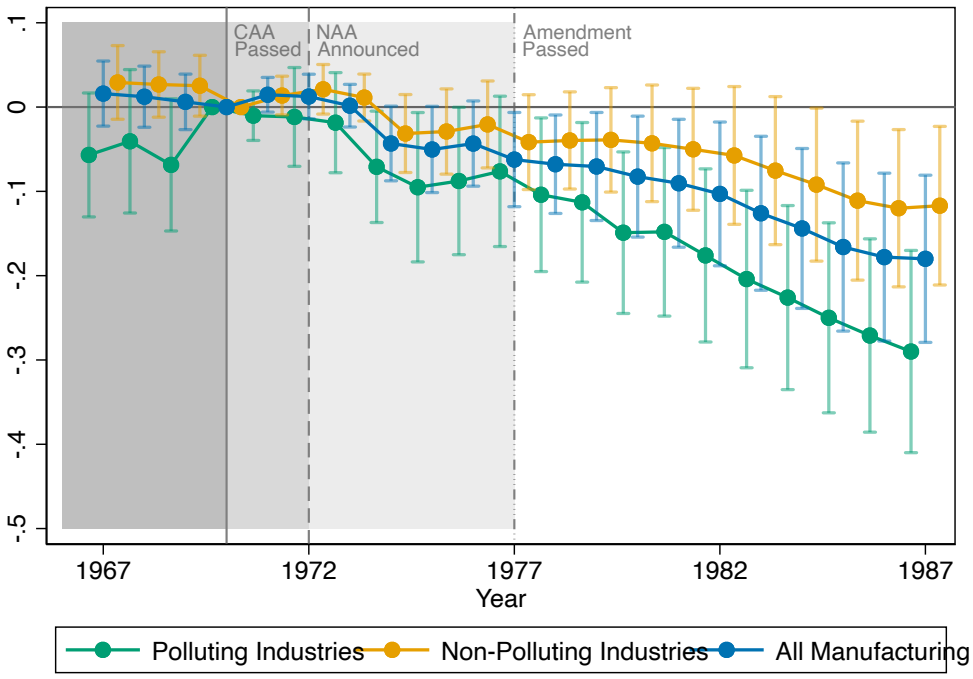
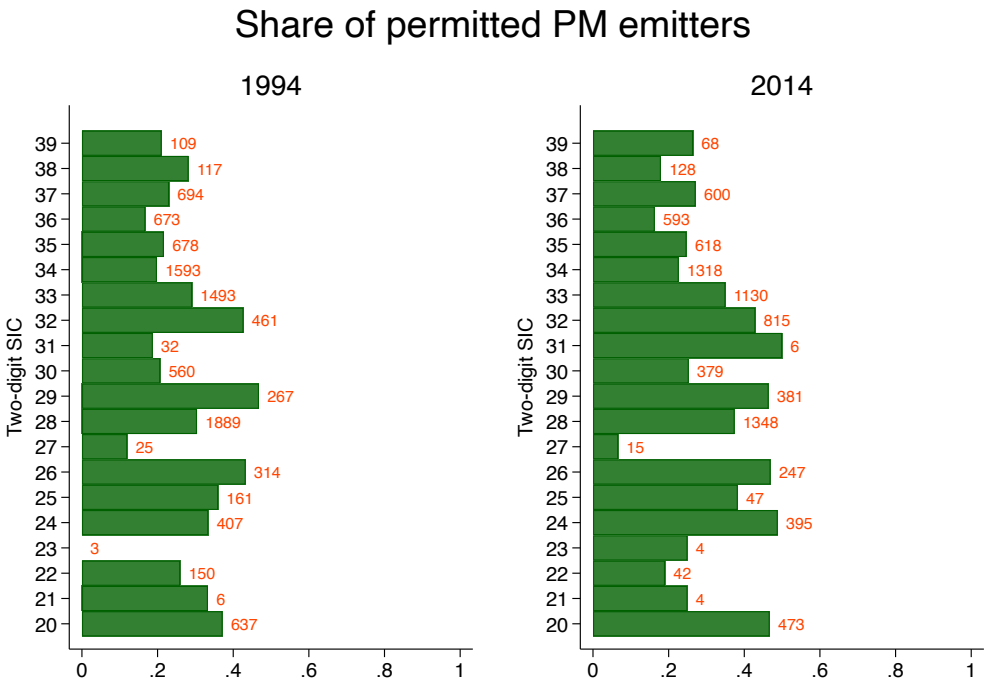


Figure A4: AFS Permit Data



# of PM emitters in industry with emissions > 0 on top of column

Figure A5: Wage Effects of Nonattainment

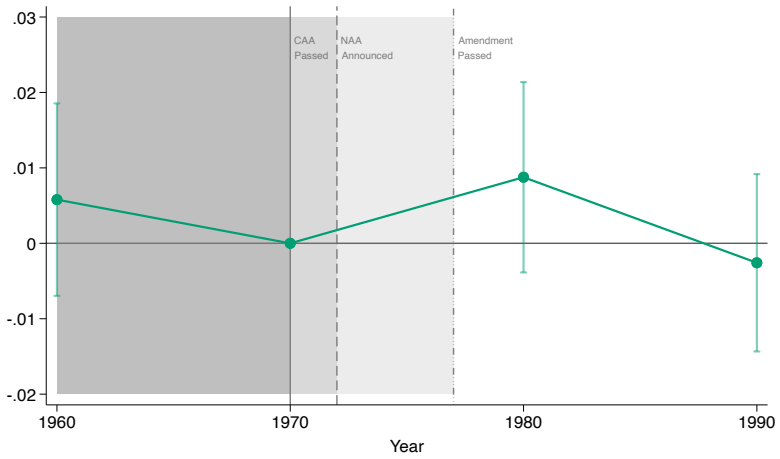
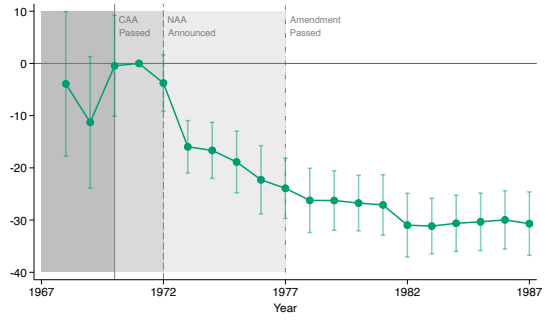
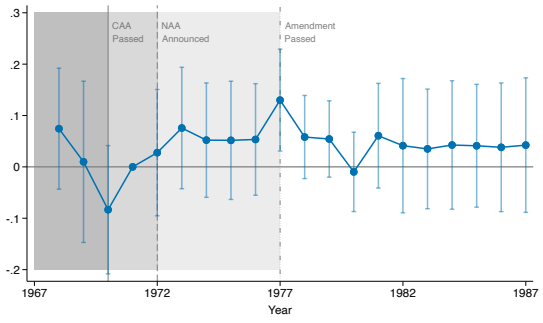


Figure A6: Pollution Effects

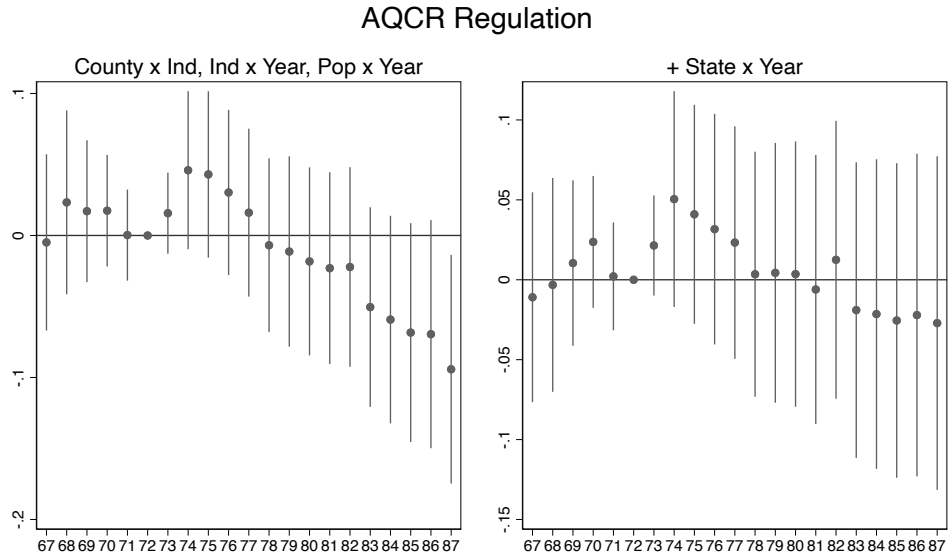


(A) Effect of Nonattainment on TSP Pollution



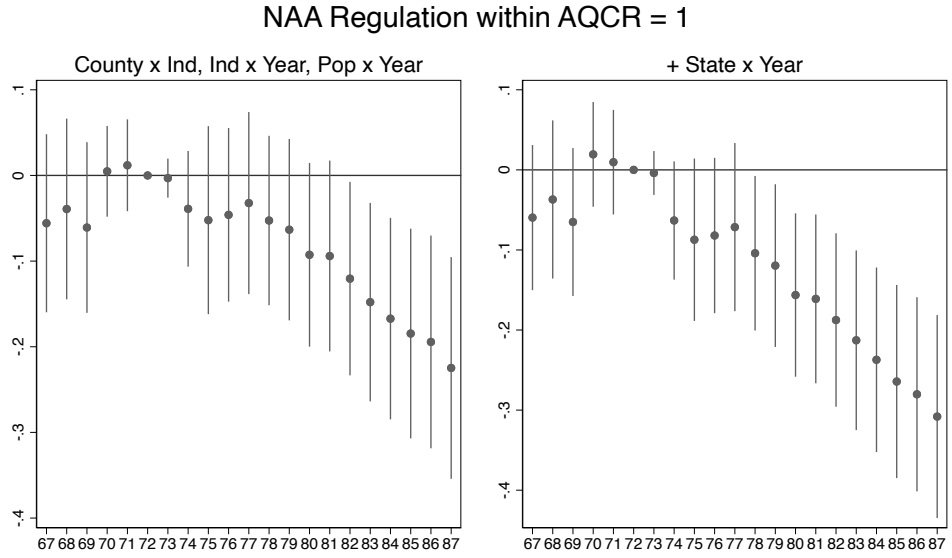
(B) Spatial leakage Effect on TSP Pollution

Figure A7: Effects of Nonattainment using AQCR Treatment



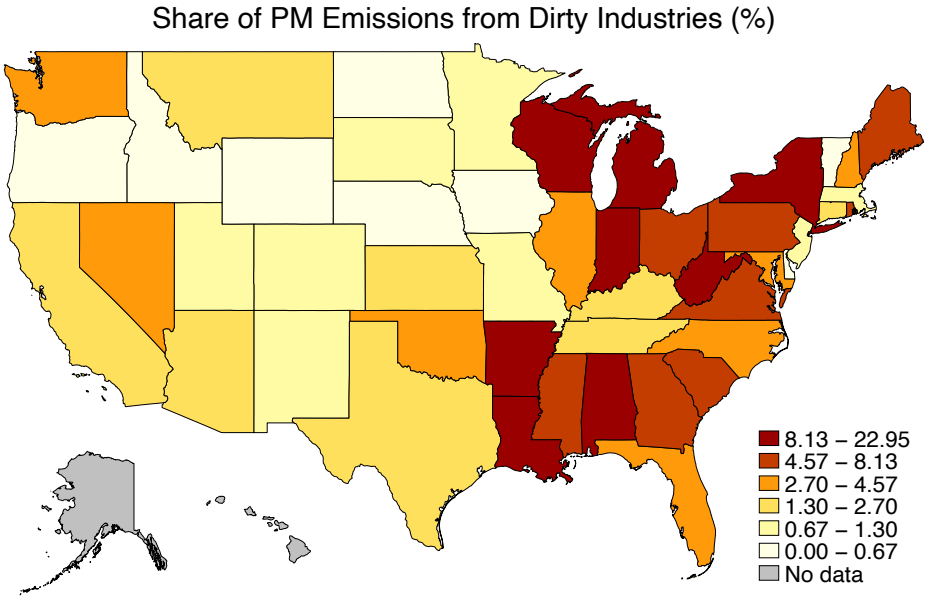
Notes: This figure reports county-level employment effects of the Clean Air Act using an alternative treatment definition based on Air Quality Control Regions (AQCRs). Counties located in nonattainment AQCRs are defined as treated, while counties in attainment AQCRs serve as the control group. Estimates are based on PPML event-study regressions that include county-sector, sector-year, and state-year fixed effects, as well as population-by-year interactions. Standard errors are clustered at the state level. Using AQCRs to define treatment produces smaller and noisier effects, reflecting limited within-state regulatory variation. As a result, we report event studies both with and without state-year fixed effects.

Figure A8: Within AQCR Treatment Effect



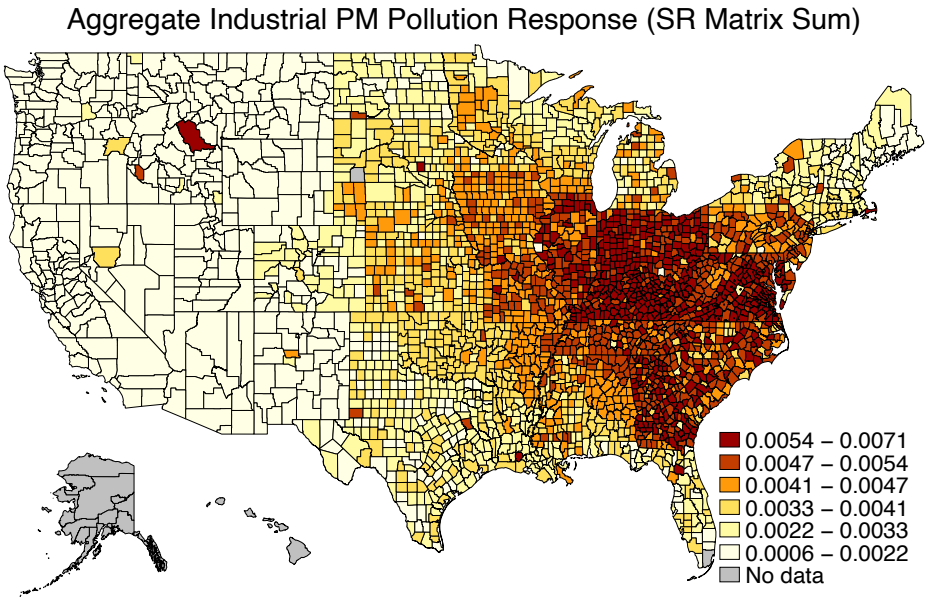
Notes: This figure reports county-level employment effects of the Clean Air Act when restricting the sample to counties located in nonattainment Air Quality Control Regions (AQCRs). Treated counties are defined using monitor-based TSP nonattainment status as in the main analysis. By focusing on the subset of counties within nonattainment AQCRs, we assess whether treatment effects are driven by within-AQCR variation. Estimates are based on PPML event-study regressions that include county-sector, sector-year, and state-year fixed effects, and control for population-by-year interactions. Standard errors are clustered at the state level.

Figure A9: Share of PM Emissions from Dirty Industries



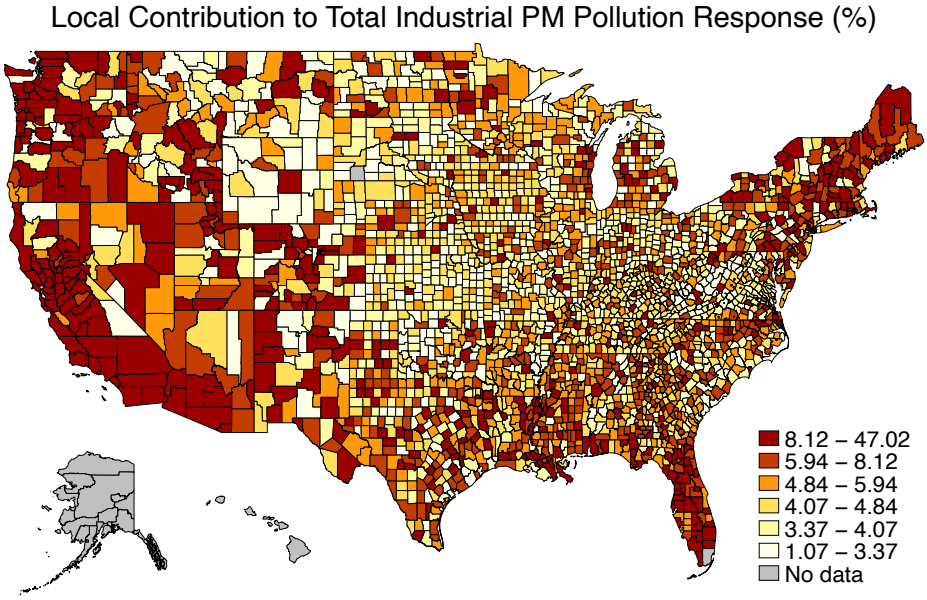
Notes: This figure reports the state-level share of PM emissions from dirty manufacturing industries. The share is calculated as PM emissions from dirty manufacturing sectors divided by the sum of total industrial and ground-source PM emissions.

Figure A10: Aggregate Industrial PM Pollution Response



Notes: This figure plots the column sum of the industrial PM spillover–response (SR) matrix. Each element of the SR matrix quantifies how a one-unit increase in PM emissions from a source county contributes to PM pollution in a receiving county after atmospheric transport. The column sum therefore measures, for each location, the total PM pollution it receives from all industrial emission sources (including its own), excluding ground sources.

Figure A11: Local Contribution to Total Industrial PM Pollution Response



Notes: This figure plots the ratio of the diagonal element to the column sum of the industrial PM spillover–response (SR) matrix. The SR matrix describes how PM emissions in each county contribute to PM pollution in all locations through atmospheric transport. The diagonal element represents the self-impact (local pollution retained within the same county), while the column sum measures the total pollution that a location receives from all sources. A higher ratio indicates that a larger share of pollution in that location originates from its own emissions, implying a more locally contained or isolated pollution pattern.