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

E. Mark Curtis
Wake Forest University

Weiting Miao
Duke University

Felix Samy Soliman
University of Zurich

Juan Carlos Suárez Serrato
Stanford GSB & NBER

Daniel Yi Xu
Duke Univeristy & NBER

March 2025

Abstract

How large is geographic leakage resulting from place-based environmental policy? We study this question in the context of the landmark US Clean Air Act Amendments. Our paper makes three primary contributions. First, using modern event-study techniques and confidential US Census data, we revisit seminal results characterizing the effects of this environmental regulation on directly regulated plants and industries. Second, we extend prior research by quantifying leakage to unregulated regions and identifying multi-unit firm networks as a key conduit for this leakage. Third, we integrate these findings into an industry spatial equilibrium model that captures both within-firm and cross-location leakage. The model quantifies the economic cost of the regulation, evaluates the contribution of multi-unit firms to regional leakage, and highlights the role of the Clean Air Act in redistributing industrial production across the US. Our analysis reveals that approximately 40% of the geographic leakage we observe is driven by within-firm reallocation, highlighting the critical role of multi-unit firms in shifting economic activity across regions.

Keywords: Clean Air Act, environmental regulation, multi-unit firms
JEL Codes: Q52, R12, L25

Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2998 (CBDRB-FY24-P2998-R11198; CBDRB-FY25-0184). We thank audiences at Duke University, Stanford University, Atlanta Fed, Center for Economic Studies of the US Census Bureau, University of Kentucky, Notre Dame, Wake Forest, IIPF, Princeton University, Kansas City Fed, Richmond Fed, Minneapolis Fed and LSE Environment Week for helpful comments.

1 Introduction

A central question in the study of environmental regulation is the degree to which regulated economic activity is shifted to unregulated domains. Leakage may occur when policies target establishments based on size or location, or impact only a subset of plants within a firm. Failing to account for leakage may bias estimates of the economic effects of important policies and misrepresent their distributional consequences.

This paper studies the direct and leakage effects of regulations in the context of a landmark environmental legislation: the Clean Air Act. The policy restricts manufacturing activity in counties that exceed the National Ambient Air Quality Standard, a federal pollution standard intended to protect human health.

Four main challenges have prevented prior studies from providing a comprehensive analysis of the direct and indirect effects of environmental regulation. First, the presence of leakage complicates the estimation of treatment effects.[1] Second, command and control regulations often disincentivize investment, but do not target existing operations. As such, focusing on a shorter time horizon produce results that fail to capture longer-run extensive margin responses such as entry and exit. Third, to properly measure leakage effects, it is crucial to contend with the fact that a significant fraction of industrial output occurs in plants that are part of multi-unit firms and may therefore more easily be able to shift production to unregulated regions. Finally, studies of leakage typically face omitted variable bias because differences in environmental regulation are often correlated with other characteristics of regulated jurisdictions. In particular, policy endogeneity can lead researchers to incorrectly conclude that environmental regulation does not shift the location of industrial activity (Copeland, Shapiro, and Taylor, 2022).

In this paper, we overcome these challenges by combining new empirical evidence with an industry spatial equilibrium model that features intra-national trade and multi-unit production. We first use confidential plant- and firm-level data from the US Census Bureau to provide new empirical evidence of how plants and firms responded to the Clean Air Act over a 20 year period. To capture important long-run adjustments, such as plant exit and

[1] Indeed, the first generation of papers studying the Clean Air Act did not directly address leakage effects (e.g., Becker and Henderson, 2000; Greenstone, 2002).

reallocation of activity within firms, we provide new event-study analyses that capture plant and firms responses to the policy. By linking regulated plants to unregulated sister plants in the same firm, our analyses capture the potential for within-firm leakage, a critical margin given that multi-unit firms were responsible for 80% of the output of regulated industries during this period (Dunne, Roberts, and Samuelson, 1988). Using event-studies, we find that, relative to unregulated plants, those in areas subject to regulation experience declines in employment and sales of 26% and 30%, respectively. Our analyses also document that a significant fraction of these changes is driven by extensive margin responses, highlighting the importance of analyses that incorporate entry and exit decisions. We then show that multi-unit firms respond to the policy by increasing their economic activity in unregulated plants. To complement these new plant- and firm-level results, we provide new estimates of the direct and geographic leakage effects at the county-level. These results show that, over a 20 year period, employment in regulated areas decreased by 25.2%, relative to non-regulated areas. At the same time, areas that were geographically closer to highly regulated regions experienced positive spillover effects and saw increases in employment.

While these new empirical results contribute to our understanding of the effects of this important regulation, we are careful to interpret them as relative changes that capture the effects of the Clean Air Act on regulated and unregulated plants. To separately capture the direct and indirect effects of the policy and quantify its aggregate impact, we build an equilibrium model that quantifies geographic leakage through intra-national trade as well as through ownership networks of multi-unit firms. The calibrated model shows that the regulation was quantitatively equivalent to a 5% reduction in the local productivity of regulated areas. These local productivity shocks impact both regulated and non-regulated areas: indeed, a decomposition of the differences-in-differences estimates implied by the model shows that 55% of the overall effects are driven by declines in economic activity in regulated areas and 45% by increases in the economic activity of non-regulated areas. Our analyses also show that a model with multi-unit firms and within-firm substitution of production is crucial to matching the estimated within-firm and cross-location spillovers. The model characterizes the effects of the regulation on the geographic spread of polluting industries, with the regulation explaining a third of the relative decline in geographic concentration between 1963 and 1987. Finally, the model quantifies the aggregate effects of the regulation as a 1.3% decline in the production of polluting industries.

We develop these results in two steps. We first use data from the Census of Manufactures and an event-study approach to revisit seminal estimates of the effects of the Clean Air Act on regulated plants using data for a longer horizon. Relative to unregulated plants, plants in areas subject to the regulation experience a 30% decline in plant output over 20 years. We find similar declines in other measures of economic activity, such as employment and energy use, and we show that exit among plants in multi-unit firms is a key driver of these results. To measure within-firm leakage, we then compare regulated firms that differ in their share of pre-regulation employment subject to the regulation. Relative to firms with low exposure, those with higher exposure see increases in the output of unregulated plants in their firm network.

We complement our evidence of within-firm reallocation with new estimates of the geographic leakage effects of the regulation using publicly-available County Business Patterns data (Eckert et al., 2020). To measure county-level indirect exposure, we calculate how much regulated employment each county is surrounded by, weighing surrounding counties inversely according to geographic distance (Adao, Arkolakis, and Esposito, 2019). Our estimates imply that counties at the 75th percentile of the exposure distribution see a 3% increase in employment relative to counties at the 25th percentile.

In a second step, we build an industry spatial equilibrium model with detailed geographic resolution, multi-plant production, and intra-national trade. The model guides our interpretation of our empirical difference-in-difference estimates and evaluates the aggregate output loss attributable to the Clean Air Act. Through the lens of our calibrated model, rationalizing the relative employment decline in regulated areas requires a 5% productivity decline in those locations, 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.

Using the model, we disentangle the direct effects captured by the difference-in-difference coefficients into the actual impacts on regulated areas and the leakage effects on unregulated ones. Approximately half of the observed reduction in employment in regulated areas, compared to unregulated areas, is attributable to leakage effects on the unregulated locations. Reallocation within multi-unit firms is a crucial driver of these effects. A model without multi-unit plants predicts that the employment increase in regulated areas is roughly 40% smaller. These reallocation effects also feed into changes in regional specialization. Between 1967 and 1987, manufacturing activity became less spatially concentrated. Our model suggests the Clean Air Act accounted for about a third of that effect, which demonstrates that environmental regulations can be a clear determinant of comparative advantage, a result that has been hard to demonstrate using cross-country data.

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).[2] 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

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

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.[3] 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.[4] 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).

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.[5] Relative to their work, we provide a detailed empirical

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

[4] 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.

[5] 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.

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 provide institutional details behind the environmental regulation that forms the basis of our identification strategy and modeling approach.

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.[6] Following the Earth Day 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

[6]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 failure" (Melnick, 1983).

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 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, even 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).[7] 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.[8] From these readings, 274 counties whose 1971/1972 monitor data exceeded the CAAA's Total Suspended Particulates threshold are defined as treated.[9]

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

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

[8] 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.

[9] 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).

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.

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 firm outcomes across attainment and nonattainment regions do not only capture the direct effect on regulated firms. This is because firms in attainment areas benefit from an increase in competitiveness. In addition, local market outcomes, such as production and employment, depend on equilibrium prices in both attainment and nonattainment areas. Within attainment regions, the model predicts an increase in employment and sales among unregulated plants exposed to the regulation through a regulated sister plant. This intrafirm leakage effect arises whenever the elasticity of substitution across plants within firms θ is greater than the elasticity of substitution across firms $\eta - 1$. Proofs of the results are in Appendix C.

Set-up. There are two ex-ante symmetric locations. Each location j has a unit mass of potential entrants j with firm productivity $\phi_j \sim G_j$. To become active, a potential entrant has to pay a fixed cost $\bar{f}_0$.

Upon entry, firms produce a unique variety using labor. We focus on the product market equilibrium and fix the wage $w_j = 1$ in both locations. To serve the foreign market, firms can trade to the other location and incur a constant iceberg trade cost $\tau > 1$. There is no additional fixed cost of exporting. Firms can also decide to open a plant in the other location at fixed cost $\bar{\bar{f}}_1$.

Following Tintelnot (2017), we assume that sales are comprised of a unit mass of shipments. Each plant receives a continuum of cost draws from Frechet distribution with a region-specific location parameter T_j and common scale θ. The firm chooses the lowest cost plant for each shipment. For a single plant firm located in j, marginal cost of serving market j are equal to

$$c_j^{SU_j} = \underbrace{\Gamma\left(\frac{\theta+1}{\theta}\right)}_{\Gamma_\theta}\frac{w_j}{T_j\phi}$$

and $c_{j'}^{SU} = \tau c_j^{SU}$. For a multi-unit firm, marginal cost of serving market j are equal to

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

In a symmetric baseline equilibrium with $\frac{w_j}{T_j} = \frac{w_{j'}}{T_{j'}}$ we have

$$\frac{c_j^{SU}(\phi)}{c_j^{MU}(\phi)} = \frac{1}{(1+\tau^{-\theta})^{-\frac{1}{\theta}}} > 1$$

i.e. the MU firm achieves lower marginal cost by exploiting comparative advantage within the firm.[10]

Combined with the presence of fixed costs of entry and MU production, the model produces intuitive sorting. Let $\bar{\phi}_j$ be the productivity of a firm indifferent between entry and inactive and $\bar{\bar{\phi}}_j$ the productivity of a firm indifferent between single-unit production and multi-unit production. Given CES-monopolistic competition, this set-up implies: $\bar{\phi}_j < \bar{\bar{\phi}}_j$.

Effects of Environmental Regulation. We model nonattainment as a negative, location-specific productivity shock $d\ln T_j < 0$ to an ex-ante symmetric industry equilibrium.[11] Productivity in the attainment region j' is unaffected. The following results characterize the effects of this shock to a first-order approximation.

[10] We provide a more detailed and general derivation of these cost functions in Section 6.1.

[11] 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'.

Result 1. The effect of regulation on revenue r and labor demand l of single and multi-unit plants active in j are given by

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

$$\begin{aligned} d\log r_j^{MU} = d\log l_j^{MU} &= (\eta-1)\left(\frac{1}{1+\tau^{-\theta}}d\log P_j + \frac{\tau^{-\theta}}{1+\tau^{-\theta}}d\log P_{j'}\right) \\ &+ \underbrace{[\tilde{\tau}(\eta-1)+(1-\tilde{\tau})\theta]}_{>0} d\log T_j \end{aligned}$$

where $\tilde{\tau} = \left(\left(\frac{\tau^{-\theta}}{1+\tau^{-\theta}}\right)^2 + \left(\frac{1}{1+\tau^{-\theta}}\right)^2\right) < 1$.

This result shows that the direct effect of regulation induced decline in productivity - holding prices fixed - is a decline in plant sales and employment.[12] For single-unit plants, the direct effect is proportional to the cross-firm elasticity of substitution. For multi-unit plants, it depends on a convex combination of the within and across firm elasticity. The fractions involving trade costs τ are exposure shares corresponding to the share of plant revenue stemming from sales in j and j', respectively.

Result 2. The effect of regulation on revenue and labor demand of plants in the unregulated region j' is given by

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

$$\begin{aligned} d\log r_{j'}^{MU} = d\log l_{j'}^{MU} &= (\eta-1)\left(\frac{\tau^{-\theta}}{1+\tau^{-\theta}}d\log P_j + \frac{1}{1+\tau^{-\theta}}d\log P_{j'}\right) \\ &+ [(\eta-1-\theta)(1-\tilde{\tau})]d\log T_j. \end{aligned}$$

Single unit plants in j' are only affected by the regulation through the effects of the regulation on the equilibrium price indices P_j and $P_{j'}$. For multi-unit plants, there is an additional effect: if $\theta > \eta - 1$, regulation in j leads to an increase in production of firms in j'. MU firms use their plant in j' to satisfy demand previously met through shipments from the plant in j. This effect is especially pronounced when trade costs τ are small.

[12] With labor as the only input factor and CES-monopolistic competition, labor and sales differ only up to a constant.

Characterizing the full effect of regulation within this model requires us to determine the effect on prices. The first step in this analysis is to establish the effects of regulation on entry and exit.

Result 3: The effects of nonattainment on entry and location choice are equal in magnitude and opposite in sign:

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

After the regulation, firms exit the nonattainment region, i.e., the productivity threshold for entry increases: $d\ln\bar{\phi}_j > 0$. However, this effect is offset by entry into the attainment region, where the entry threshold decreases by an equal amount. The entry effect arises because the attainment region gains in relative competitiveness. Additionally, firms head-quartered in j are more likely to open a second plant if $\theta > \eta - 1$, i.e., the productivity threshold defining MU status decreases: $d\ln\bar{\bar{\phi}}_j < 0$. The restriction $\theta > \eta - 1$ guarantees that the profits of single-unit firms are more negatively affected by a productivity decline than those of multi-unit firms.[13] At the same time, exporting becomes more attractive for firms headquartered in j', where the multi-unit threshold increases. 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.

Result 4. The effect of nonattainment on the price index is given by

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

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

[13] Whenever $\theta > \eta - 1$, sales are more substitutable within the firm, so firms can partially evade the productivity loss of regulation by selecting into multi-unit production.

$\Lambda < 1$. This holds when the market share of marginal firms is sufficiently small so that the price index is not too elastic with respect to the behavior of these firms.

Result 5. Suppose $\Lambda < 1$. Then a difference-in-difference comparison overstates the effects of nonattainment 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 and exit, partially offset by the increase in the price index in j. A similar equilibrium adjustment leads to entry in the unregulated location j'. Additionally, the within firm shift in economic activity raises labor demand among plants in multi-unit firms. Together, these effects imply an increase in labor demand $d \ln L_{j'} > 0$. Thus, comparing a regulated area to an unregulated 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, it double-counts entry and exit effects as well as within-firm relocation.

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 C). 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.

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".[14] 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.

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).[15] 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.[16] 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

[14] 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.

[15] 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.

[16] 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.

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 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.[17]

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

[17] 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).

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 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.[18] 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. Effects on the number of plants are muted. 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.[19] 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 attain-

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

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

ment 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).[20] 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 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.[21] 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 (2019) and we follow their work in additionally controlling for

[20]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.

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

$X_{cj} = \sum_{k \neq c}^{K} \frac{D_{ck}^{-\delta}}{\sum_{k' \neq c}^{K} D_{ck'}^{-\delta}} \text{Employment}_{kj1970}$ 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 (2019). 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 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 have 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 also allows us to relate our results to alternative estimators of the effects of nonattainment. In some specifications, Greenstone (2002) relies on a triple-difference design comparing clean and dirty industries, before and after regulation passed across attainment and nonattainment counties. From Figure A3, we see that this type of comparison would imply smaller effects of nonattainment since non-polluting industries decline too. We believe this comparison would understate the effects of nonattainment because non-polluting industries remain a plausible target for regulators. To illustrate this point, 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.[22] A commuting zone is considered treated if any 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.

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

6 Quantitative Model

6.1 Quantitative Spatial Equilibrium Model

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 implications from the reduced-form difference-in-difference estimates of the Clean Air Act regulations.

6.1.1 Demand

The economy has N locations. Each location m has a representative consumer with preferences given by a Cobb-Douglas aggregator across sectors

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

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 each 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

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

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.

6.1.2 Production

Since each sector is separable in terms of demand, we now abstract from s in the following.

Cost function 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[23]

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

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 $l \in Z$. The productivity distribution is assumed to be Fréchet (which depends on both firm efficiency ϕ and local condition T_l)

$$Pr(\nu_l \leq x) = exp(-(\phi T_l)^\theta (x)^{-\theta}).$$

Given the assumption of production technology, the cost distribution of sourcing from each location remains Fréchet.

$$Pr(\frac{w_l \tau_{lm}}{\nu_l} \leq c) = 1 - exp\left(\left(\frac{w_l \tau_{lm}}{\phi T_l}\right)^{-\theta} c^\theta\right).$$

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

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

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

$$c_m(\phi, Z) = \left[\int_0^1 c_m(\omega, j)^{1-\eta} dj\right]^{\frac{1}{1-\eta}} \equiv \left[\int_0^\infty c^{1-\eta} dG_m(c|\phi, Z)\right]^{\frac{1}{1-\eta}} \tag{7}$$
$$= \Gamma\left(\frac{\theta + 1 - \eta}{\theta}\right)^{\frac{1}{1-\eta}} \left(\sum_{l \in Z}\left(\frac{w_l \tau_{lm}}{\phi T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}.$$

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

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

$$p_m(\phi, Z(\omega)) = \left(\frac{\eta}{\eta-1}\right) c_m(\phi, Z(\omega)) = \left(\frac{\eta}{\eta-1}\right) \Gamma_\theta \left(\sum_{l \in Z(\omega)} \left(\frac{w_l \tau_{lm}}{\phi T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}. \tag{8}$$

Each firm has sales at market m of

$$s_m(\phi, Z(\omega)) = \underbrace{\frac{I_m}{P_m^{1-\eta}}}_{A_m} p_m(\phi, Z(\omega))^{1-\eta}. \tag{9}$$

The model also characterizes the share of sales to market m that are sourced from $l \in Z(\omega)$:

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

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

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

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

$$\pi(\phi, l(\omega), \vec{f_{l'}}(\omega)) = \max_{Z \in \mathcal{Z}} \frac{1}{\eta} \sum_m s_m(\phi, Z(\omega)) - \sum_{l' \in Z(\omega), l' \neq l} f_{l'}(\omega), \tag{11}$$

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

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 $E_l = \mu_l E$.

6.1.3 Equilibrium

Given $w_l, I_m, T_l, \tau_{lm}, G_f, G_\phi, \forall m, l = 1, ..., N$, the 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 (11).[24]

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 is rich enough to capture important geographic patterns in the US economy. After calibrating 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.

We next first describe a simplifying procedure to solve the multi-unit firm location problem for a large number of local markets. Second, we describe how we parameterize trade costs and the distributions of productivity and fixed costs. We then discuss how we calibrate key parameters using the simulated method of moments. Finally, we show that the model provides a realistic approximation of the geographic distribution of economic activity among regulated industries prior to the implementation of the CAAA.

[24]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.

6.2 Simplifying 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 correspond to attainment and nonattainment areas. In practice, we use the 1990 definition of Commuting Zones (CZs) and simulate 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}.[25]

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

$$\pi(\phi, Z) = \frac{1}{\eta}\left(\frac{\eta}{\eta-1}\Gamma_\theta\right)^{1-\eta}\phi^{\eta-1}\sum_m A_m\left[\left(\sum_{l\in Z}\left(\frac{\tau_{lm}}{T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}\right]^{1-\eta} - \sum_{l\in Z} f_l$$
$$\equiv \tilde{\eta}_\theta(\phi)^{\eta-1}\sum_m A_m\left[\left(\sum_{l\in Z}\left(\frac{\tau_{lm}}{T_l}\right)^{-\theta}\right)^{-\frac{1}{\theta}}\right]^{1-\eta} - \sum_{l\in Z} f_l, \qquad (12)$$

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 assume firms pick their plant configuration Z by solving a two-tier location choice problem. In the first stage, firms choose the best potential production location within each state according to the sourcing potential of commuting zone l, given by $\sum_m A_m\left(\frac{\tau_{lm}}{T_l}\right)^{-\theta} - f_l$. This sourcing potential reflects the profit a single-plant firm would make from choosing that commuting zone. In the second stage, firms solve the combinatorial plant location choice problem by choosing the set of states where they produce based on the potential payoff of producing in each state as determined in stage one. This second stage fully takes into account potential cannibalization effects that arise if firms locate plants in neighboring states. Although the combinatorial problem is formulated at the state level, brute-force computation remains computationally prohibitive. To accelerate computation, we leverage the submodularity property of firm

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

profits and employ squeezing and branching techniques, following the approach of Arkolakis, Eckert, and Shi (2023). The solution to this simplified choice problem deviates from the solution to the combinatorial problem across all 722 commuting zones by limiting firms to one plant per state and introducing a simple heuristic where to locate that plant within state. The benefit of this heuristic approach is that it allows us to examine the effects of the Clean Air Act at a detailed geographic level while maintaining key aspects of the location decisions faced by large, multi-plant firms.

Iterative Algorithm. We implement this decision rule using the following algorithm.

1. Take an initial guess of A_m;
2. For each firm ϕ
   (a) and for each state s, find the most attractive location $\max_{l\in s}\sum_m A_m \left(\frac{\tau_{lm}}{T_l}\right)^{-\theta} - f_l$. Denote the set of most attractive locations as N^*.
   (b) find the optimal combination of locations Z across $l \in N^*$ by solving (11).
3. For a firm with productivity ϕ at l, its expected cost of selling to market m is

$$c_m(\phi, l) = \Gamma_\theta(\phi)^{-1} \times \left(\sum_{k\in Z(\phi,l)} \left(\frac{\tau_{km}}{T_k}\right)^{-\theta} \right)^{-\frac{1}{\theta}}$$

   if the firm is active in any locations. The firm sets the price in market m as

$$p_m(\phi, l) = \frac{\eta}{\eta - 1} c_m(\phi, l).$$

4. We can then update the price index P_m as

$$P_m^{1-\eta} = \sum_l E_l \int_\phi p_m(\phi, l)^{1-\eta} f(\phi) d\phi.$$

5. Iterate until A_m converges.

In practice, this algorithm solves the equilibrium of the model including the location decisions of multi-unit firms in a computationally tractable way.

6.3 Parameterization and Estimation

We implement the model in four steps. First, we take expenditure shares directly from the data. Second, we assign the elasticities of substitution across varieties and within the firm to values commonly used in the literature. Third, we set trade costs to values implied by estimated gravity models in the literature. Finally, we parameterize the distributions of fixed costs and productivity and we estimate these parameters using the simulated method of moments.

Step 1: Expenditure Shares. We assume that the mass of potential firms in each location, E_l, is proportional to the number of establishment in each location.[26] In the absence of granular commuting zone-level spending data, we impute I_m by combining county-level personal income from the BEA with the state-level spending on the four polluting sectors from the Commodity Flow Survey. Letting s be state and c county, we compute

$$I_m = \sum_{c \in m} \frac{Income_c}{\sum_{c \in s} Income_c} I_s,$$

where I_s is state-level spending from the Commodity Flow Survey and $Income_c$ is county-level income from the BEA.[27] 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.

Step 2: Elasticities of Substitution. We set the elasticity of substitution across varieties to $\eta = 4$, in line with consensus estimates from the gravity literature (Head and Mayer, 2014). To calibrate the shape parameter of the Fréchet distribution for plant productivity draws, we rely on estimates from prior literature literature and pick a value of $\theta = 8$. Tintelnot (2017) uses $\theta = 7$ because it lies within the range of productivity dispersion estimates reported in Eaton and Kortum (2002). Head and Mayer (2019) estimate $\theta = 7.7$ based on sourcing decisions of multinational car manufacturers.

[26] Given the low share of multi-unit firms, the spatial distribution of the number of firms and the number of establishments are highly correlated.

[27] 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**	**Value**	**Source**
Demand elasticity		$\eta = 4$	
Product cost distribution	Fréchet	$\theta = 8$	
Trade cost	$\tau_{lm} = dist_{lm}^{\beta_\tau}$	$\beta_\tau = 0.375$	CFS Data
Fixed cost at home	$f_l(\omega) \overset{iid}{\sim} logN(\mu_{f_0}, \sigma_f)$	$\mu_{f_0} = -4.0$	$\sim 10\%$ of sales
Firm productivity	$\phi \overset{iid}{\sim} logN(0, \sigma_\phi)$	0.645	MU sales share
Fixed cost at away	$f_{l'}(\omega) \overset{iid}{\sim} logN(\mu_{f_1}, \sigma_f)$	$(1.99, 1.01)$	MU share/#Plants

Step 3: Trade Costs. Trade costs, τ_{lm}, depend on distance d_{lm} through $\tau_{lm} = (d_{lm}/d_{norm})^{\beta_\tau}$ for $d_{lm} > d_{norm}$; distances below d_{norm} incur no trade cost. The normalization distance, d_{norm}, is set at 50 miles to align with the observed level of out-of-state trade, where 67% of consumption originates from producers located outside the state. We use a value of β_τ that is consistent with estimates of gravity models in the literature. Disdier and Head (2008) report that the elasticity of trade relative to distance, based on 103 papers, ranges from 0.04 to -2.33. Because the industries we study are relatively heavier, we select a trade elasticity in the upper range of -1.5, which in our model implies a value of $\beta_\tau = 0.375$ across CZs.

Step 4: Estimation of Fixed Costs and Productivity Distributions. We assume that firms' core efficiency is log-normally distributed $\phi \sim LogN(0, \sigma_\phi)$. Similarly, we model the fixed costs of entry in domestic and other locations by assuming that $f_l \sim LogN(\mu_{f_0}, \sigma_f)$ and $f_{l'} \sim LogN(\mu_{f_1}, \sigma_f)$, where $\mu_{f_0} < \mu_{f_1}$. Because our model is static, it is unable to separately identify entry costs for home and other locations. We therefore set $\mu_{f_0} = 4.0$, such that the mean fixed cost share of sales is 5% among plants in home locations.

We use the simulated methods of moment to estimate the firm productivity dispersion (σ_ϕ) and fixed costs parameters (μ_{f_1}, σ_f). We denote the parameter vector as $\psi \equiv \{\sigma_\phi, \mu_{f_1}, \sigma_f\}$. For a candidate value of ψ, we simulate the model and compute the following moments: (1) share of multi-unit firms; (2) average number of plants per multi-unit firm; and (3) Share of sales from multi-unit firms. Our estimate of ψ minimizes the criterion function $[m_d - m(\psi)]'W[m_d - m(\psi)]$, where m_d are the data moments, $m(\psi)$ are the simulated model moments, and W is the weighting matrix. Panel B of Table 1 shows the estimated

Table 2: Moments in Data and Model

	Data	**Model**
Targeted:		
MU Share	0.055	0.055
Average number of plants per MU	3.72	3.72
Share of production from MU	0.785	0.788
Untargeted:		
Output share of top 1% firm		59.4%
Output share of top 5% firm		78.4%
Output share of top 10% firm		84.3%

parameters. The implied mean and median share of fixed cost to sales for plants in non-home locations are 12.3% and 12.9%, respectively.

Model Fit. Table 2 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. The correlation between the model-simulated and actual production is 74.8%. The model shows a slightly less geographical concentrated pattern of production compared to the data. This discrepancy may arise because the model assumes uniform local productivity across all locations. A model that also calibrates local productivities would perfectly match the model's production distribution with the observed spatial data.

7 Quantifying the Economic Effects of Environmental Regulations

We now use our estimated model to simulate the distribution of economic activity before and after the introduction of the CAAA. We assume that the regulation imposes a productivity discount on regulated locations, resulting in their productivity being adjusted to $\beta_T T_l$, where $\beta_T < 1$. Figure 7 displays a map marking regulated and unregulated areas at the commuting zone level. For a given value of β_T, we solve the equilibrium before and after the regulation and replicate the empirical analyses from Section 5 using data generated by the model. We then solve for the value of β_T such that the model-implied difference-in-difference estimates match the plant-level direct effect of regulation estimated in Section 5.

Panel A of Table 3 compares the estimated reduced-form results with the model-implied values using a value of $\beta_T = 0.95$. Column (3) shows that the location-level effects of nonattainment on sales is -36%, with a standard error of 7%.[28] While this estimate is larger than the estimated direct spatial effect, it falls within the confidence interval of the empirical counterpart. Through the lens of the model, the entry margin is responsible for the difference between the plant-level and the spatial direct effect of regulation. Regulated areas see a decline in entry, amplifying the effect of regulation beyond what is implied by effects on incumbent plants.

We can assess the empirical performance of our model by comparing model-implied to empirically estimated leakage and within firm reallocation effects. These empirical moments were left untargeted in our calibration strategy. The first column shows that the model qualitatively replicates, but quantitatively understates the within firm reallocation of economic activity from regulated to unregulated areas (-1.4% versus -2.9% in the data). Turning to leakage effects, we implement our empirical strategy of estimating within firm leakage effects in the model and find the model closely replicates the data. Why can our model successfully replicate this untargeted moment? As shown in section 4, the within-firm leakage depends on the difference between within (θ) and across firm substitution ($\eta - 1$). We use standard values from the literature for these parameters and find the implied leakage closely matches the data. Consistent with the theory, we have also solved the model for $\theta = \eta - 1$, and find zero within firm leakage effects in that case.

Turning to spatial leakage, we construct the indirect exposure to regulation for each location as in our empirical analysis, setting $\delta = 1.5$ to align with the value used in the model. The estimated effects imply that a location at the 75th percentile of the exposure distribution experiences a 1.8% increases in output compared to a location at the 25th percentile. The empirically estimated leakage is substantially larger at 9.1%.[29] In on-going work, we are investigating whether a model with differential productivity prior to regulation

[28] Through the lens of our model, employment and sales only differ by constant that is unaffected by regulation.

[29] To align our empirical analysis with geography in the model, the estimates reported in Table 3 are estimated by aggregating the CBP data to the commuting zone by sector level.

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

	With-in Firm Reallocation	Direct Effect		leakage Effect	
		Plant	Spatial	Firm	Spatial
A. Data vs. Model					
Empirical	-0.0292	-0.3517	-0.2901	0.5382	0.0911
	(0.0026)	(0.0717)	(0.0529)	(0.2064)	(.0457)
Model	-0.0143	-0.2609	-0.3751	0.5332	0.0179
	(0.0016)	(0.00141)	(0.0126)	(0.0876)	(0.00981)
B. Decomposition					
Change in Treated		-0.2146	-0.1991		
Change in Control		0.0464	0.1760		

Notes: The coefficients on the spatial leakage effect equal the actual coefficient from the regression multiplied by the interquartile range of the indirect exposure variable.

better matches these leakage estimates.

Decomposing Difference-in-Differences Estimates. As discussed in Section 4, coefficients from difference-in-differences models reflect a relative effect between the treated and control groups. Our model allows us to decompose this coefficient into the specific effects on regulated locations and unregulated locations. The decomposition shows a 19.9% decrease in sales for regulated locations, accounting for 55% of the estimated effect, and a 17.6% increase in sales for unregulated locations, representing 45% of the estimated effect. We can apply the same decomposition to plant-level direct effect coefficients, with the results presented in Panel B of Table 3. Consistent with the insights from Section 4, we find that the estimated difference-in-differences coefficients overstate the negative impacts on economic activity in nonattainment areas. At the same time, these results show that attainment areas see economic benefits from the regulation.

Multi-Unit Firms and the Effects of Regulation. Our model allows us to more precisely quantify the role of within firm leakage for the reallocation of production to unregulated areas. Column 1 of Table 4 shows these partially regulated firms have a much higher sales share at baseline. Larger firms are mechanically more likely to be exposed to the regulation

Table 4: Effects of Regulation on Plants in Unregulated Areas

	Sales Share	Changes in Sales	Intensive	Extensive
Unregulated Firms	23%	6%	98%	2%
Regulated MU Firms	77%	23%	38%	62%

through their larger plant network, explaining this discrepancy. Beyond their larger size prior to regulation, unregulated plants of regulated firms are also significantly more sensitive to regulation than those part of entirely unregulated firms (column 2). The extensive margin is especially important for these differences, as illustrated by columns 3 and 4. Overall, these results suggest that incorporating multi-unit firms substantially affects the amount of reallocation to unregulated regions. In line with this discussion, a calibrated version of our model with $\theta = \eta - 1$, i.e. abstracting from within firm reallocation, features substantially smaller increases in sales among plants in unregulated areas (11 versus 18%).

Regional and Aggregate Price Changes. Through the lens of the model, price indexes are a direct measure of the consumption costs of the regulation. Given fixed expenditure, real consumption is determined by dividing expenditure by the market price. Model simulations indicate that prices, including those in both nonattainment and attainment locations, increase across most locations. Prices in attainment areas, where output increases, also rise because these markets source from other regulated locations that have experienced a productivity loss. While most locations experience price increases, 52 out of 722 locations in our model see a decline in prices. This decline is driven by increases in the production of the home or adjacent locations, which saves on trade costs.

Figure 9 plots the percentage changes in prices for each CZ. The West Coast and Mid-Atlantic regions experience the largest increases in prices, whereas the central areas of the country face smaller losses or even experience price declines. The aggregate output loss across the entire economy is 1.3%. This number is derived under the assumption of uniformly distributed local productivity. If regulation disproportionately affects locations with higher productivity, the output loss could be more significant.

Table 5: Percent Decline from 1967 to 1987

	Dirty Industry	Clean Industry	Model
Std across CZs	-26%	-13%	-4.1%
Top 5% CZ share	-23%	-12%	-3.6%
Top 10% CZ share	-17%	-9%	-2.8%

The table shows percent declines in different measures of geographic concentration across commuting zones (CZ). "Dirty Industry" refers to four polluting sectors considered in our empirical analysis. "Clean Industry" refers to the remaining manufacturing industries. "Model" indicates the predicted decline in induced by the regulation counterfactual where we impose a 5% productivity decline in regulated areas.

Environmental Regulation and the Decline in Regional Concentration. Between 1967 and 1987, the geographical concentration of manufacturing falls significantly. Columns 1 and 2 of Table 5 shows that for both clean and dirty sectors, the regional concentration of employment, as measured by declines in the standard deviation of employment shares across commuting zones. The share of employment accounted for by 5% and 10% largest commuting zones falls by a similar amount in percent terms. Notably, these declines are more pronounced in dirty than in clean industries. Column 3 shows that the model predicts roughly 1/6 of the overall decline in concentration in polluting industries or roughly 1/3 of the relative decline. The latter may be a more appropriate quantification of the effects of regulation because it nets out common forces affecting the decline in concentration as measured from changes in clean industries.[30] Why can regulation lead to a decline in regional concentration? The Clean Air Act targets more densely populated areas that are hubs of manufacturing activity. By reallocating activity towards less urban areas, regulation reduces geographic concentration.

These effects also speak to the pollution haven effect whereby environmental regulation co-determines the geography of production in pollution intensive industries (Cherniwchan, Copeland, and Taylor, 2017). Prior to regulation, manufacturing activity was centered around population centers. By increasing the cost of pollution in these areas, the Clean

[30] Clean industries may also be affected by regulation, but Figure A3 shows these effects are substantially smaller than for polluting industries.

Air Act shifts the comparative advantage in pollution intensive production towards more rural regions.

8 Conclusion

Environmental regulations that target regions can create substantial reallocation through both market and within-firm leakage. This paper improves our understanding of the magnitude of these leakage effects by providing new empirical evidence on the effects of the CAAA. Using confidential data from the Census Bureau, we provide new results highlighting the importance of considering reallocation along firm ownership networks. Additionally, these results show that the CAAA had prolonged and growing effects on regulated firms, surpassing estimated effects in previous studies. In particular, entry and multi-unit adjustments play key role in long-run responses. Using newly-harmonized data on local economic activity, we also provide new evidence of leakage effects across counties and commuting zones.

To interpret these new empirical results and to quantify the direct, indirect, and aggregate effects of the CAAA, we build a spatial equilibrium model with intra-national trade and multi-plant location choice. The model shows that simple difference-in-differences comparisons exaggerate the negative effects of regulations, since both regulated and non-regulated regions are affected in equilibrium. On net, we find that slightly more half of the estimated effects on local markets are driven by declines in the output of regulated regions, with the rest being due due to increases in the output of non-regulated regions. Finally, we find that, while most regions see a consumption cost from the regulations, these costs are dispersed across locations depending on whether a given location is regulated as well as the regulation status of neighboring regions. Overall, we find that the consumption cost of the CAAA was on the order of 1.3% of consumption. By providing a more detailed quantification of the geographic distribution of the costs of environmental regulations, our model moves us one step closer to evaluating the welfare costs of placed-based regulations across the US.

References

Acharya, Viral V., Abhishek Bhardwaj, and Tuomas Tomunen. 2023. "Do firms mitigate climate impact on employment? Evidence from US heat shocks." *Working Paper* .

Adao, Rodrigo, Costas Arkolakis, and Federico Esposito. 2019. "General equilibrium effects in space: Theory and measurement." *Working Paper* .

Arkolakis, Costas, Fabian Eckert, and Rowan Shi. 2023. "Combinatorial Discrete Choice: A Quantitative Model of Multinational Location Decisions." Tech. rep., National Bureau of Economic Research.

Auffhammer, Maximilian, Antonio M Bento, and Scott E Lowe. 2009. "Measuring the effects of the Clean Air Act Amendments on ambient PM10 concentrations: The critical importance of a spatially disaggregated analysis." *Journal of Environmental Economics and Management* 58 (1):15–26.

Becker, Randy and Vernon Henderson. 2000. "Effects of air quality regulations on polluting industries." *Journal of political Economy* 108 (2):379–421.

Borusyak, Kirill and Peter Hull. 2023. "Nonrandom exposure to exogenous shocks." *Econometrica* 91 (6):2155–2185.

Campolmi, Alessia, Harald Fadinger, Chiara Forlati, Sabine Stillger, and Ulrich J. Wagner. 2024. "Designing effective carbon border adjustment with minimal information requirements. Theory and empirics." .

Castro-Vincenzi, Juanma. 2023. "Climate hazards and resilience in the global car industry." Tech. rep., Technical report, Working Paper.

Chen, Jiafeng and Jonathan Roth. 2023. "Logs with zeros? Some problems and solutions."." *Quarterly Journal of Economics* .

Cherniwchan, Jevan, Brian R Copeland, and M Scott Taylor. 2017. "Trade and the environment: New methods, measurements, and results." *Annual Review of Economics* 9 (1):59–85.

Chow, Melissa C, Teresa C Fort, Christopher Goetz, Nathan Goldschlag, James Lawrence, Elisabeth Ruth Perlman, Martha Stinson, and T Kirk White. 2021. "Redesigning the longitudinal business database." Tech. rep., National Bureau of Economic Research.

Clay, Karen, Akshaya Jha, Joshua A Lewis, and Edson R Severnini. 2021. "Impacts of the Clean Air Act on the Power Sector from 1938-1994: Anticipation and Adaptation." Working Paper 28962, National Bureau of Economic Research. URL http://www.nber.org/papers/w28962.

Copeland, Brian R., Joseph S. Shapiro, and M. Scott Taylor. 2022. "Globalization and the Environment." *Handbook of International Economics: International Trade, Volume 5* :61–146.

Cropper, Maureen, Nicholas Muller, Yongjoon Park, and Victoria Perez-Zetune. 2023. "The impact of the clean air act on particulate matter in the 1970s." *Journal of Environmental Economics and Management* 121:102867. URL https://www.sciencedirect.com/science/article/pii/S0095069623000852.

Cui, Jingbo, Chunhua Wang, Zhenxuan Wang, Junjie Zhang, and Yang Zheng. 2023. "Carbon Leakage within Firm Ownership Networks." *Available at SSRN 4514971* .

Currie, Janet, John Voorheis, and Reed Walker. 2023. "What caused racial disparities in particulate exposure to fall? New evidence from the Clean Air Act and satellite-based measures of air quality." *American Economic Review* 113 (1):71–97.

Disdier, Anne-Célia and Keith Head. 2008. "The puzzling persistence of the distance effect on bilateral trade." *The Review of Economics and statistics* 90 (1):37–48.

Dunne, Timothy, Mark J Roberts, and Larry Samuelson. 1988. "Patterns of firm entry and exit in US manufacturing industries." *The RAND journal of Economics* :495–515.

Eaton, Jonathan and Samuel Kortum. 2002. "Technology, geography, and trade." *Econometrica* 70 (5):1741–1779.

Eckert, Fabian, Teresa C. Fort, Peter K. Schott, and Natalie J. Yang. 2020. "Imputing missing values in the US Census Bureau's county business patterns." .

Eckert, Fabian, Ka-leung Lam, Atif R Mian, Karsten Müller, Rafael Schwalb, and Amir Sufi. 2022. "The early county business pattern files: 1946-1974." *Working Paper* .

Fajgelbaum, Pablo D, Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar. 2019. "State taxes and spatial misallocation." *The Review of Economic Studies* 86 (1):333–376.

Fowlie, Meredith L. 2009. "Incomplete environmental regulation, imperfect competition, and emissions leakage." *American Economic Journal: Economic Policy* 1 (2):72–112.

Gibson, Matthew. 2019. "Regulation-Induced Pollution Substitution." *The Review of Economics and Statistics* 101 (5):827–840. URL https://doi.org/10.1162/rest_a_00797.

Giroud, Xavier, Simone Lenzu, Quinn Maingi, and Holger M Mueller. 2021. "Propagation and amplification of local productivity spillovers." *Working Paper* .

Golosov, Mikhail, John Hassler, Per Krusell, and Aleh Tsyvinski. 2014. "Optimal taxes on fossil fuel in general equilibrium." *Econometrica* 82 (1):41–88.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy* 110 (6):1175–1219. URL https://doi.org/10.1086/342808.

Greenstone, Michael, John A List, and Chad Syverson. 2012. "The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing." Working Paper 18392, National Bureau of Economic Research. URL http://www.nber.org/papers/w18392.

Hafstead, Marc A.C. and Roberton C. Williams. 2018. "Unemployment and environmental regulation in general equilibrium." *Journal of Public Economics* 160:50–65. URL https://www.sciencedirect.com/science/article/pii/S0047272718300136.

Hanna, Rema. 2010. "US Environmental Regulation and FDI: Evidence from a Panel of US-Based Multinational Firms." *American Economic Journal: Applied Economics* 2 (3):158–89. URL https://www.aeaweb.org/articles?id=10.1257/app.2.3.158.

Head, Keith and Thierry Mayer. 2014. "Gravity equations: Workhorse, toolkit, and cookbook." In *Handbook of international economics*, vol. 4. Elsevier, 131–195.

———. 2019. "Brands in motion: How frictions shape multinational production." *American Economic Review* 109 (9):3073–3124.

Hollingsworth, Alex, Taylor Jaworski, Carl Kitchens, and Ivan J Rudik. 2022. "Economic Geography and the Efficiency of Environmental Regulation." Working Paper 29845, National Bureau of Economic Research. URL http://www.nber.org/papers/w29845.

Isen, Adam, Maya Rossin-Slater, and W Reed Walker. 2017. "Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970." *Journal of Political Economy* 125 (3):848–902.

Melnick, R Shep. 1983. *Regulation and the courts: The case of the Clean Air Act*. Brookings Institution Press.

Murphy, Joshua Dennis. 2017. *The Costs, Benefits, and Efficiency of Air Quality Regulation*. University of Toronto PhD Dissertation.

Roberts, Marc J. and Susan O. Farrell. 1978. "The political economy of implementation: The Clean Air Act and stationary sources." *Approaches to Controlling Air Pollution* 152:156–160.

Sanders, Nicholas J. and Charles Stoecker. 2015. "Where have all the young men gone? Using sex ratios to measure fetal death rates." *Journal of Health Economics* 41:30–45. URL https://www.sciencedirect.com/science/article/pii/S0167629614001520.

Shapiro, Joseph S and Reed Walker. 2018. "Why is pollution from US manufacturing declining? The roles of environmental regulation, productivity, and trade." *American Economic Review* 108 (12):3814–3854.

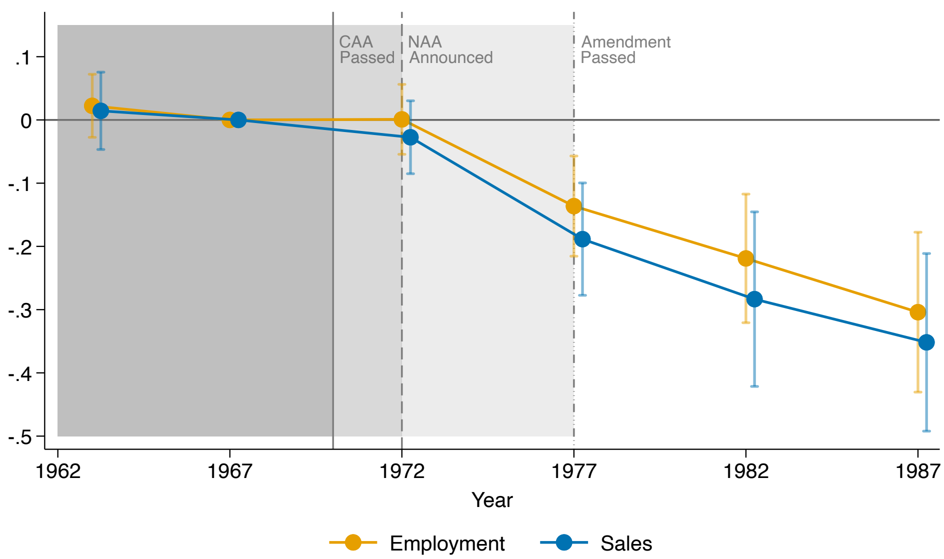
Shapiro, Joseph S. and Reed Walker. 2023. "Is Air Pollution Regulation Too Stringent? Evidence from US Offset Markets." Working Papers 23-27, Center for Economic Studies, U.S. Census Bureau. URL https://ideas.repec.org/p/cen/wpaper/23-27.html.

Suárez Serrato, Juan Carlos and Philippe Wingender. 2014. "Estimating the Incidence of Government Spending." Mimeo.

Tintelnot, Felix. 2017. "Global production with export platforms." *The Quarterly Journal of Economics* 132 (1):157–209.

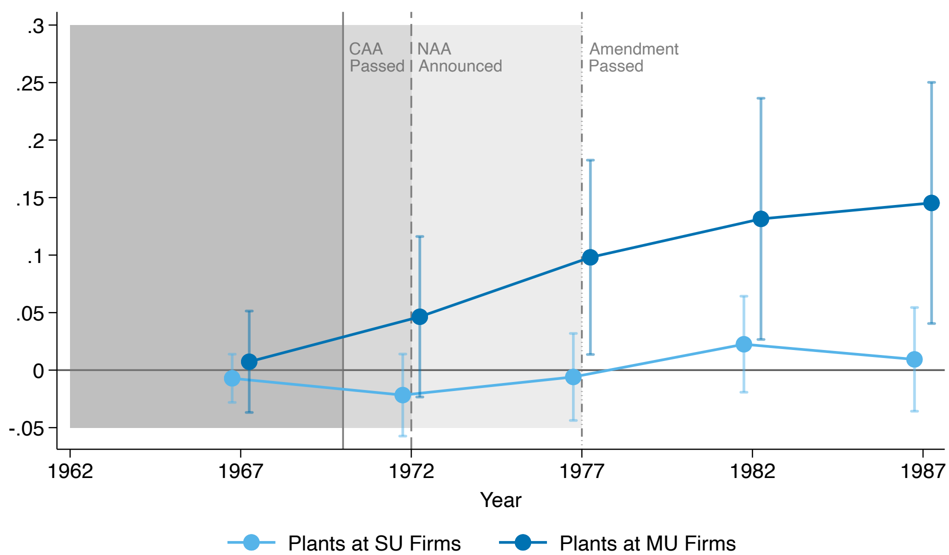
Walker, W Reed. 2013. "The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce." *The Quarterly journal of economics* 128 (4):1787–1835.

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

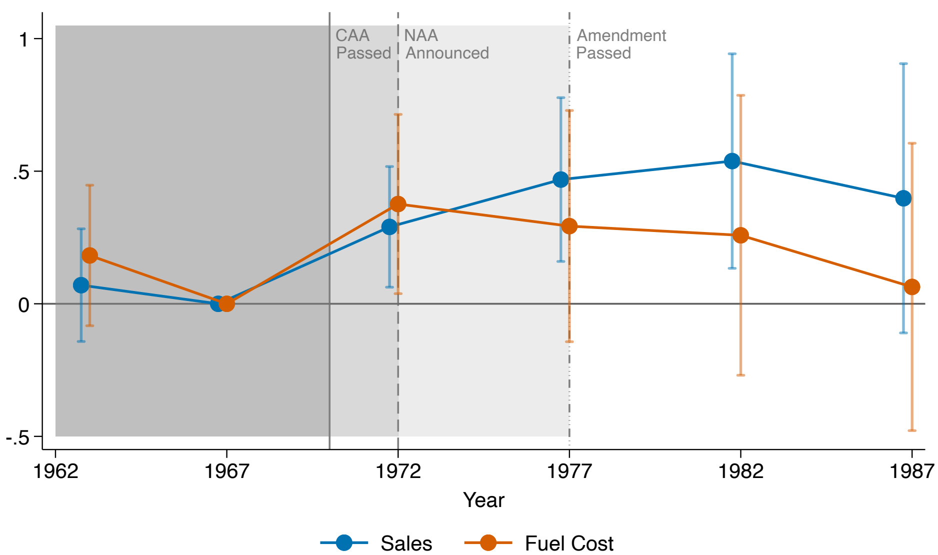


Notes: Figure 2 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on probability of exit. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CM, LBD and EPA Greenbook.

Figure 3: Within Firm leakage Effects

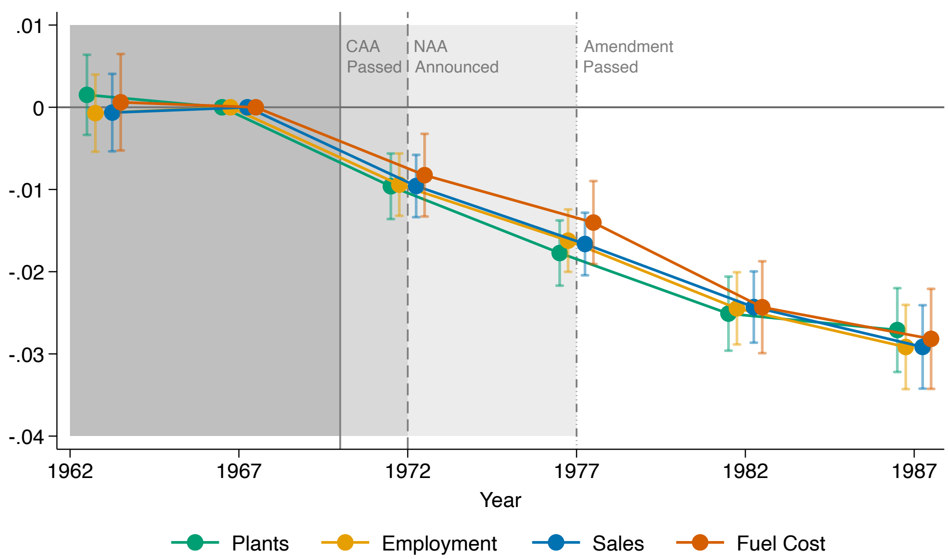
(A) Within Firm leakage: Plants, Employment

(B) Within Firm leakage: Sales, Fuel Cost



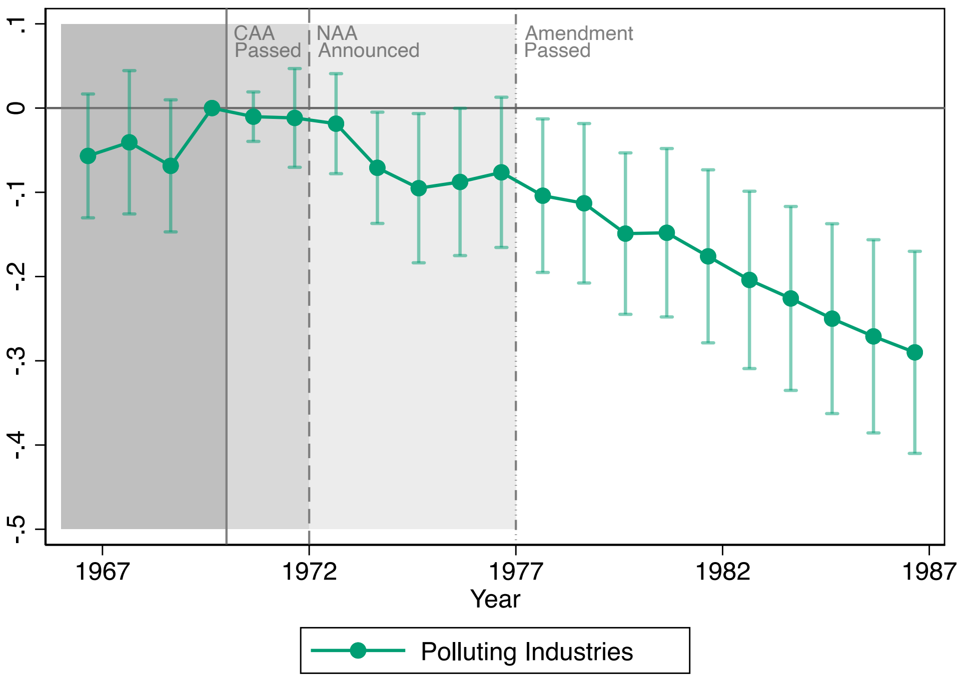
Notes: Figure 3 displays Dynamic DD estimates and 95% confidence intervals describing the within firm leakage effect of the nonattainment standards. Standard errors are clustered at the firm level. Panel (A) displays within firm leakage effects for number of plants and employment while Panel (B), shows 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



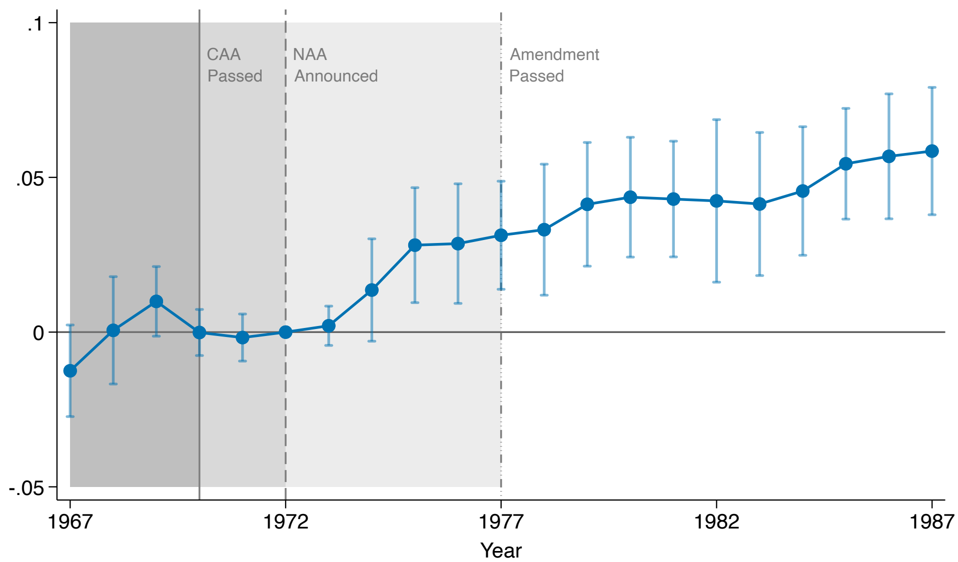
Notes: Figure 4 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on regulated firms' activity share in NAA counties, with standard errors computed using a robust variance estimator. *Source:* Authors' calculations based on CM, LBD and EPA Greenbook.

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



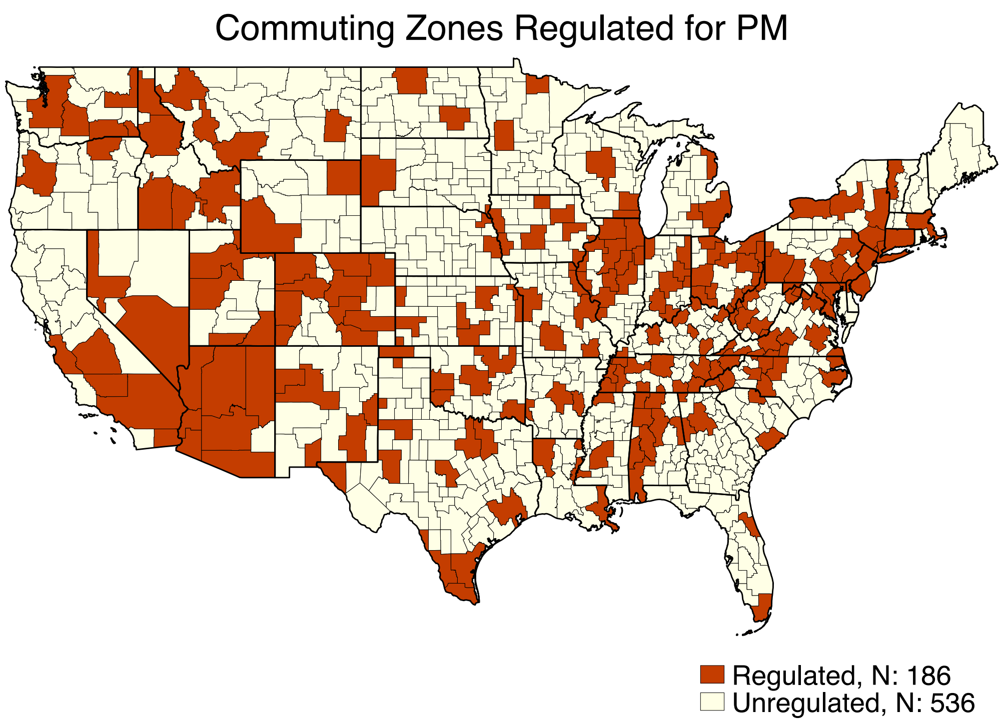
Notes: Figure 5 displays dynamic DD estimates and 95% confidence intervals describing the effect of NAA on county-level employment. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CBP and EPA Greenbook.

Figure 6: Spatial leakage Effects of Nonattainment



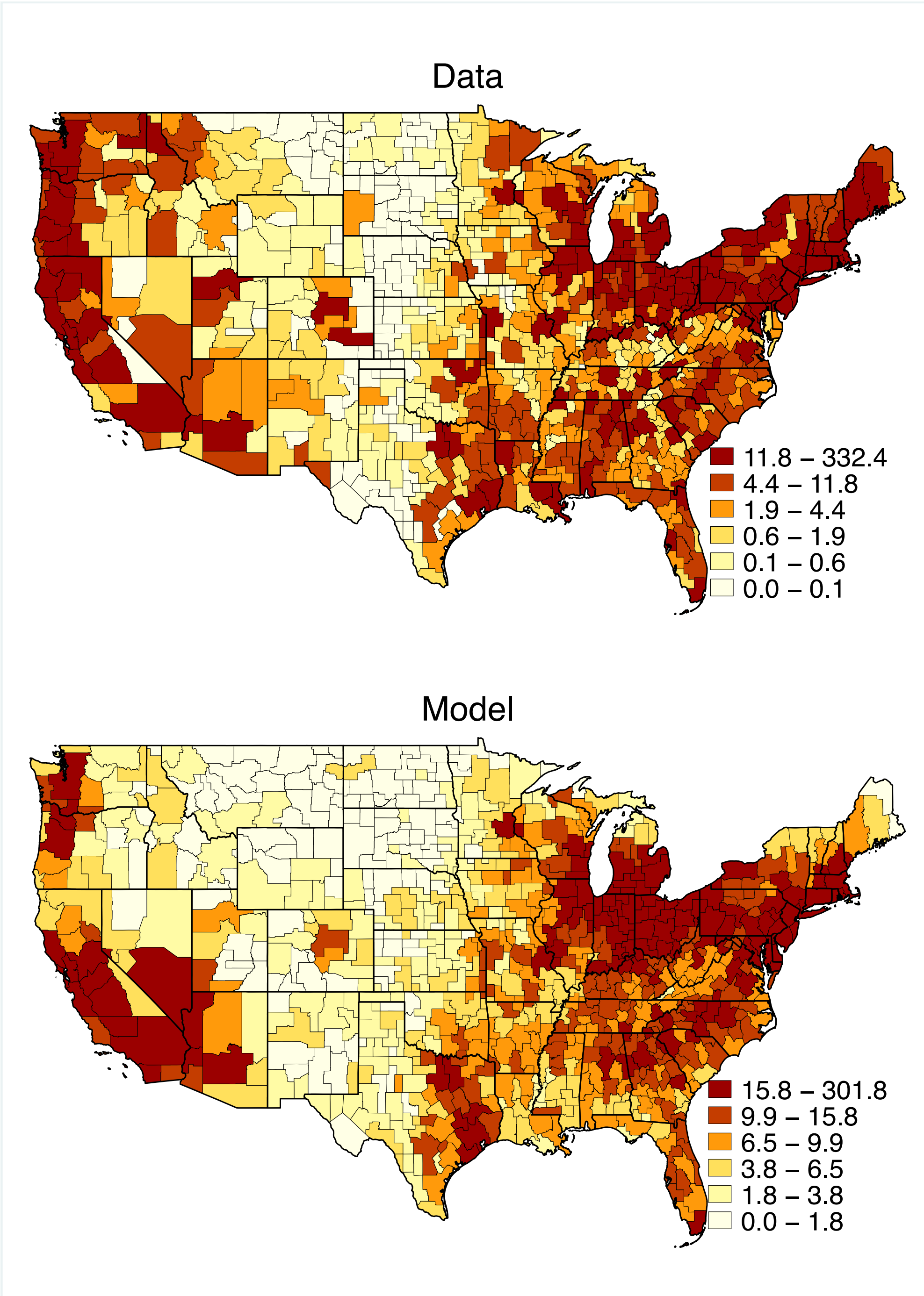
Notes: Figure 6 displays dynamic DD estimates and 95% confidence intervals describing the spatial leakage effect of NAA. Standard errors are clustered at the county level. *Source:* Authors' calculations based on CBP and EPA Greenbook.

Figure 7: Map of Regulation at the Commuting Zone Level



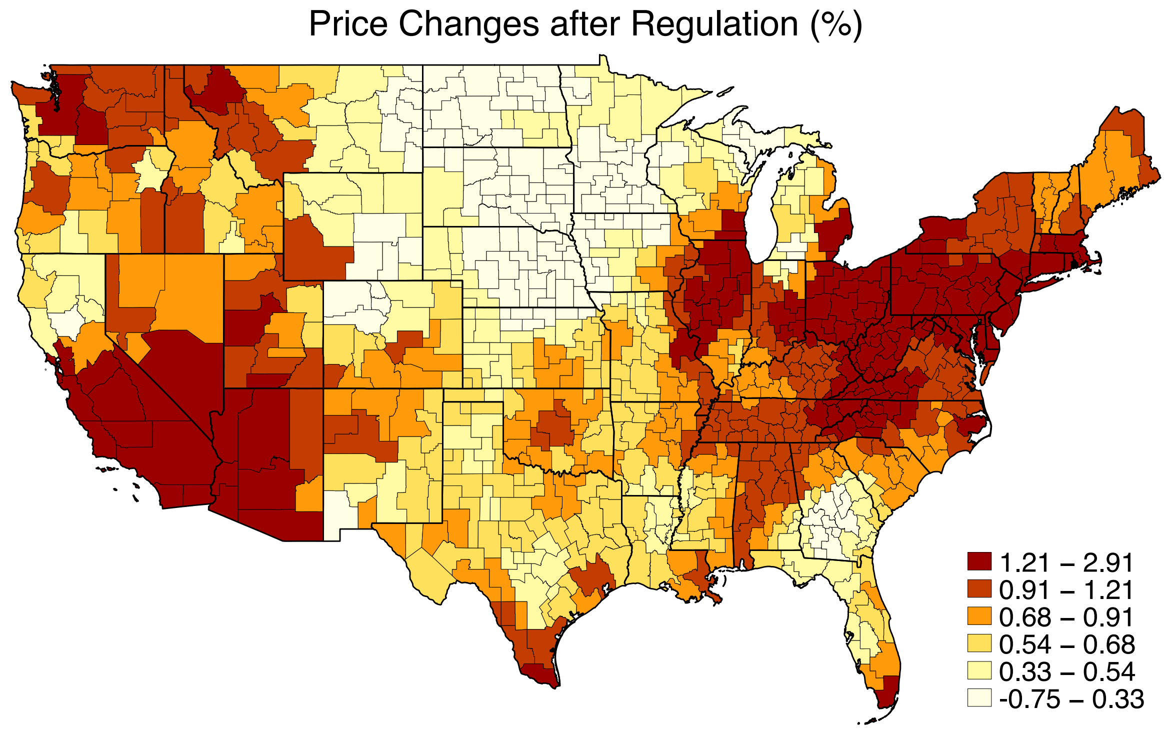
Notes: Figure 7 displays a map of the regulated and unregulated commuting zones.

Figure 8: Spatial Distribution of Production in Data and Model



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.

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 C details the derivation of our motivating two-region model. Appendix D 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.

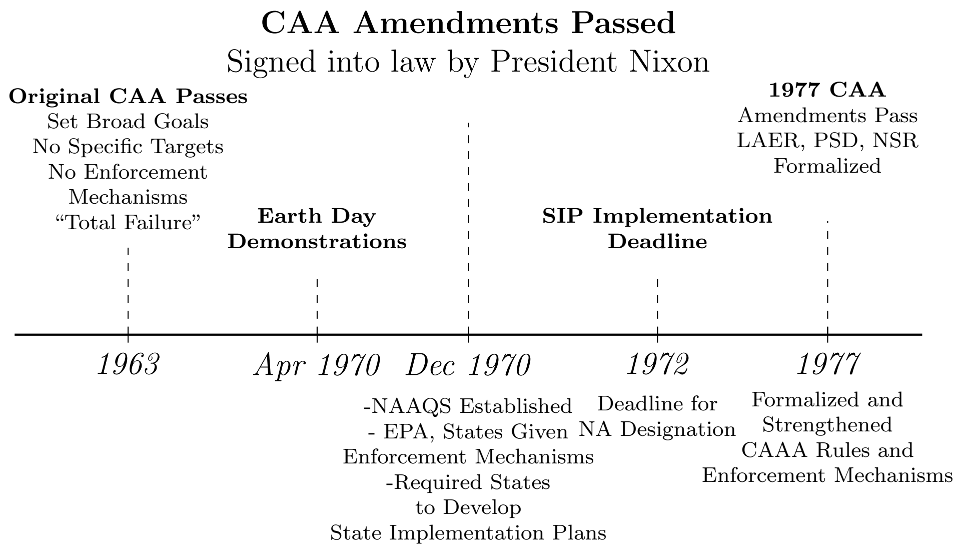
B CAAA History and Details

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 Derivations Two-Region Model

Derivation Results 1 and 2. Specializing the formula for plant-level revenue to the special case of two symmetric regions, we have that sales for single unit firms are equal to

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

Deflating by the price and deflating by productivity ϕT_j to go from quantity to input requirement shows that labor demand is proportional to revenue. Log-linearizing, this expression around a symmetric equilibrium gives the result. Summing across destination markets, total sales of a MU plant in j are

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

Sales and labor demand continue to be proportional by the logic pointed out in footnote 8 in Tintelnot (2017): Plants in the model can be thought of as setting a price equal to the mark-up $\frac{\eta}{\eta-1}$ over marginal costs. This ensures labor demand and sales continue to be proportionally constant. Log-linearizing this expression gives

$$\begin{aligned}
d\log r_j^{MU} = {} & \frac{1}{\left(\frac{T_j^\theta}{(T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_j^{\eta-1} + \frac{\tau^{-\theta} T_j^\theta}{(\tau^{-\theta} T_j^\theta + T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_{j'}^{\eta-1} \right)} \\
& \times \Bigg[(\eta-1) \left(\frac{T_j^\theta}{(T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_j^{\eta-1} d\ln P_j + \frac{\tau^{-\theta} T_j^\theta}{(\tau^{-\theta} T_j^\theta + T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}}} P_{j'}^{\eta-1} d\ln P_{j'} \right) \\
& + \frac{\theta T_j^\theta (T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}} P_j^{\eta-1} + (\eta-1-\theta)(T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}-1} T_j^\theta T_j^\theta P_j^{\eta-1})}{(T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{2\frac{\theta+1-\eta}{\theta}}} d\ln T_j \\
& + \frac{\theta \tau^{-\theta} T_j^\theta (T_j^\theta + \tau^{-\theta} T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}} P_j^{\eta-1} + (\eta-1-\theta)(\tau^{-\theta} T_j^\theta + T_{j'}^\theta)^{\frac{\theta+1-\eta}{\theta}-1} \tau^{-\theta} T_j^\theta \tau^{-\theta} T_j^\theta P_{j'}^{\eta-1})}{(\tau^{-\theta} T_j^\theta + T_{j'}^\theta)^{2\frac{\theta+1-\eta}{\theta}}} d\ln T_j \Bigg].
\end{aligned}$$

Using $T_j = T_{j'}$ and $P_j = P_{j'}$, the expression can be simplified to

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

Sales for plants in j' are equal to

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

Log-linearizing gives:

$$d\ln r_{j'}^{MU} = (\eta-1)\frac{\tau^{-\theta}}{1+\tau^{-\theta}} d\ln P_j + (\eta-1)\frac{1}{1+\tau^{-\theta}} d\ln P_{j'} + (\eta-1-\theta)\frac{2\tau^{-\theta}}{(1+\tau^{-\theta})^2} d\ln T_j.$$

Derivation Results 3 and 4.

Firm ϕ pays fixed cost $\bar{f}_0$ for its first plant and $\bar{f}_1$ for its second plant. We normalize expenditure in both locations $E_j = E_{j'} = w_j = w_j' = 1$ - our results hold for any symmetric value. Conditional on its mode of operation, standard arguments imply that CES-monopolistically single unit firms earn profits

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

The marginal plant in j has productivity $\bar{\phi}_j$ defined by

$$\pi_j^{SU}(\bar{\phi}_j) = 0 \implies \bar{\phi}_j = \left(\frac{\eta}{\eta-1}\Gamma_\theta \frac{w_j}{T_j}\right)(\eta \bar{f}_0)^{\frac{1}{\eta-1}} \left(P_j^{\eta-1} + P_{j'}^{\eta-1}\tau^{1-\eta}\right)^{\frac{1}{1-\eta}}.$$

A firm operating with two plants earns profits

$$\pi^{MU}(\phi) = \phi^{\eta-1}\frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta}\left(P_j^{\eta-1}(c_j^{MU})^{1-\eta} + P_{j'}^{\eta-1}(c_{j'}^{MU})^{1-\eta}\right) - (\bar{f}_0 + \bar{f}_1).$$

The marginal MU firm has productivity $\bar{\bar{\phi}}_j$ defined by

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

which can be solved for as

$$\bar{\bar{\phi}}_j = \frac{\eta}{\eta-1}(\eta \bar{f}_1)^{\frac{1}{\eta-1}} \left(P_j^{\eta-1}\left((c_j^{MU})^{1-\eta} - (c_j^{SU})^{1-\eta}\right) + P_{j'}^{\eta-1}\left((c_{j'}^{MU})^{1-\eta} - (\tau c_j^{SU})^{1-\eta}\right)\right)^{\frac{1}{1-\eta}}.$$

Log-linearized equilibrium

In a symmetric equilibrium, the log-linearized cutoffs can be expressed as

$$d\ln \bar{\phi}_j = -d\ln T_j - \omega^{SU} d\ln P_j - (1-\omega^{SU})d\ln P_{j'}$$

and

$$d\ln \bar{\phi}_{j'} = -(1-\omega^{SU})d\ln P_j - \omega^{SU} d\ln P_{j'}$$

where $\omega_{SU} = \frac{1}{1+\tau^{1-\eta}} > \frac{1}{2}$ is share of total sales to home market for a single unit firm. To derive the cutoff for MU firms, the log-linearized cost functions are

$$d\ln c_j^{MU} = -\frac{1}{1+\tau^{-\theta}} d\ln T_j.$$

We also have have $d\ln c_j^{MU} + d\ln c_{j'}^{MU} = -d\ln T_j$. The effect of a productivity shock on production cost for single unit firms in j is

$$d\ln c_j^{SU} = -d\ln T_j.$$

Putting these results together, we have

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

and

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

The difference between $d\ln \bar{\bar{\phi}}_j$ and $d\ln \bar{\bar{\phi}}_{j'}$ reflects fact that for firms with a plant in j', the productivity of single plant status is not directly affected by $d\ln T_j$, hence the increase in productivity in j makes MU status in j' unambiguously more attractive. For firms in j the partial effect is ambiguous. If the elasticity of substitution within plants is larger across plants, then a productivity improvement in j makes having a second plant in j' relatively less valuable because in that case profits of MU firms are relatively less sensitive to productivity in j.

Proof. Log-linearizing around a symmetric equilibrium we get

$$
\begin{aligned}
d\ln\bar{\bar{\phi}}_j = &-\frac{\left((c_j^{MU})^{1-\eta}-(c_j^{SU})^{1-\eta}\right)d\ln P_j+\left((c_{j'}^{MU})^{1-\eta}-(\tau c_j^{SU})^{1-\eta}\right)d\ln P_{j'}}{(c_j^{MU})^{1-\eta}-(c_j^{SU})^{1-\eta}+(c_{j'}^{MU})^{1-\eta}-(\tau c_j^{SU})^{1-\eta}}\\
&+\frac{(c_j^{MU})^{1-\eta}d\ln c_j^{MU}-(c_j^{SU})^{1-\eta}d\ln c_j^{SU}}{(c_j^{MU})^{1-\eta}-(c_j^{SU})^{1-\eta}+(c_{j'}^{MU})^{1-\eta}-(\tau c_j^{SU})^{1-\eta}}\\
&+\frac{(c_{j'}^{MU})^{1-\eta}d\ln c_{j'}^{MU}-(\tau c_j^{SU})^{1-\eta}d\ln c_j^{SU}}{(c_j^{MU})^{1-\eta}-(c_j^{SU})^{1-\eta}+(c_{j'}^{MU})^{1-\eta}-(\tau c_j^{SU})^{1-\eta}}
\end{aligned}
$$

In a symmetric equilibrium we can use $\frac{c_j^{SU}}{c_j^{MU}}=\frac{1}{(1+\tau^{-\theta})^{-\frac{1}{\theta}}}$ to define

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

as share of extra sales an SU firm realizes in j from switching to MU status ($1-\Delta>\frac{1}{2}$ is the share realized in j' i.e. the SU firm in j would gain disproportionately in j' from switching to MU).

For the second part, we additionally use $d\ln c_j^{MU}=-\mu_{jj}d\ln T_j$ where μ_{jj} is share of sales to j accounted for by plant in j and $d\ln c_j^{SU}=-d\ln T_j$ and $d\ln c_j^{MU}+d\ln c_{j'}^{MU}=-d\ln T_j$ as well as $c_j^{MU}=c_{j'}^{MU}$ □

Price index. For a unit mass of potential entrants, and around a symmetric equilibrium, the log-linearized price index is

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

The direct effect of a productivity change is proportional to the share of consumption produced in j (coming from domestic SU firms, and MU firms from j and j'). The second, third and fourth row line from net entry and net changes in MU status. Those effects are proportional to the market shares of these "marginal" firms.
An equivalent expression for the price index in j' is

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

Adding these two together, we get

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

Defining

$$
C = \frac{\left[p^{SU}(\bar{\bar{\phi}}_j)^{1-\eta}(1+\tau^{1-\eta}) - 2p^{MU}(\bar{\bar{\phi}}_j)^{1-\eta} \right] - p_j^{SU}(\bar{\phi}_j)^{1-\eta}(1+\tau^{1-\eta})}{P_j^{1-\eta}(1-\eta)}
$$

and using

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

we get

$$
(d\ln P_j + d\ln P_{j'})(1+C) = -d\ln T_j(1+C)
$$

which also implies

$$
d\bar{\phi}_j + d\bar{\phi}_{j'} = d\bar{\bar{\phi}}_j + d\bar{\bar{\phi}}_{j'} = 0.
$$

Since the base level of these variables are the same in a symmetric equilibrium, this result obtains from the result for log derivatives. With this result, we get the following simplification

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

We can rewrite the log-linearized entry cutoffs

$$
d\ln\bar{\phi}_j = -\omega^{SU} d\ln T_j - (2\omega^{SU}-1)d\ln P_j
$$

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

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

where $\tilde{\gamma} = \frac{1}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - 1 + (1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}} - \tau^{1-\eta}} > 0$ Now we can plug those into the price index to get

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

$$d\ln P_j \underbrace{(1+\alpha(\bar{\phi})(2\omega^{SU}-1)+\alpha(\bar{\bar{\phi}})(1-2\Delta))}_{>0} = -(S_D+\alpha(\bar{\phi})\omega^{SU}+\alpha(\bar{\bar{\phi}})\tilde{\gamma})d\ln T_j$$

which gives the result $d\ln P_j = -\Lambda d\ln T_j$ with $\Lambda > S_D > 0 \iff (\alpha(\bar{\phi})(2\omega^{SU}-1)+\alpha(\bar{\bar{\phi}})(1-2\Delta))S_D < (\alpha(\bar{\phi})\omega^{SU}+\alpha(\bar{\bar{\phi}})\tilde{\gamma})$ which holds because $\omega^{SU} > (2\omega^{SU}-1) \iff \omega^{SU} < 1$ and $\tilde{\gamma} > 1-\Delta > 1-2\Delta$ which holds under our maintained assumption of $1+\tau^{1-\eta}-\left(1+\tau^{-\theta}\right)^{-\frac{1-\eta}{\theta}} \iff \theta > \eta - 1$.

Log-linearized Equilibrium Characterized

Suppose $\Lambda < 1$ and $\theta > \eta - 1$. Then a negative productivity shock $d\ln T_j < 0$ raises prices in j and j' with

$$d\ln P_{j'} = -(1-\Lambda)d\ln T_j > 0 \;\; \textbf{and} \;\; d\ln P_j = -\Lambda d\ln T_j > 0$$

A negative productivity shock leads to exit of SU firms

$$d\ln\bar{\phi}_j = \omega^{SU}\Lambda d\ln T_j + (1-\omega^{SU})(1-\Lambda)d\ln T_j - d\ln T_j > 0$$

and a larger share of MU firms in j.

$$d\ln\bar{\bar{\phi}}_j = \Delta\Lambda T_j + (1-\Delta)(1-\Lambda)d\ln T_j + \frac{(1+\tau^{1-\eta})-(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}}}{(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}}-1+(1+\tau^{-\theta})^{-\frac{1-\eta}{\theta}}-\tau^{1-\eta}}d\ln T_j < 0$$

These entry responses are offset in j'.

Derivation Result 5

Labor demand analysis In a symmetric equilibrium, labor demand in j comes from domestic SU firms as well as domestic and foreign MU firms. Write these as

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

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

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

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 $d\bar{\bar{\phi}}_j = -d\ln\bar{\bar{\phi}}_{j'}$ and $l(\bar{\bar{\phi}}_j)^{MU} = l(\bar{\bar{\phi}}_{j'})^{MU}$.

Similarly we log-linearize the labor demand for j'

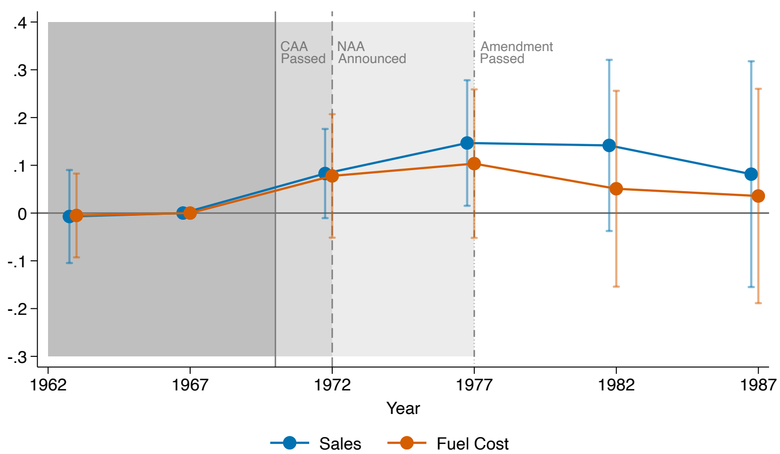
$$
\begin{aligned}
d\ln L'_j = & \underbrace{(1-\alpha^{SU})(1-\omega_{MU})(\eta-1-\theta)d\ln T_j}_{\text{Intrafirm Leakage Effect>0}} \\
& + \underbrace{(\eta-1)\left[\alpha^{SU}((1-\omega_{SU})d\ln P_j + \omega_{SU} d\ln P_{j'}) + (1-\alpha^{SU})((1-\omega_{MU})d\ln P_j + \omega_{MU} d\ln P_{j'}\right]}_{\text{Product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

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

D Appendix Figures

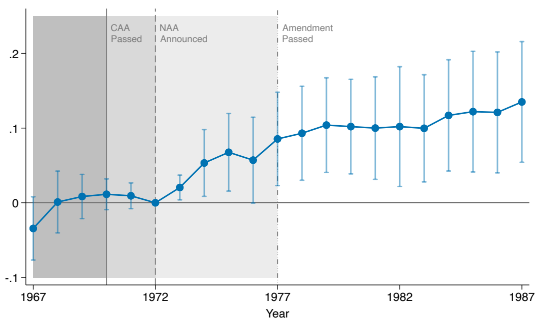
Figure A1: Within Firm leakage Effects: Discrete Exposure Variable

(A) Employment and Number of Plants

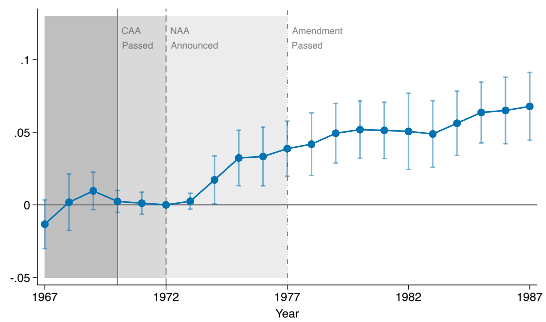


(B) Sales and Cost of Fuels

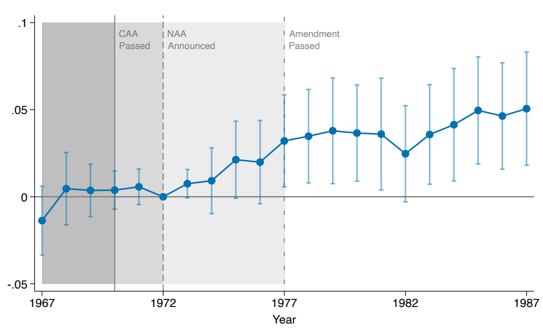
Figure A2: Spatial leakage: Robustness



(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

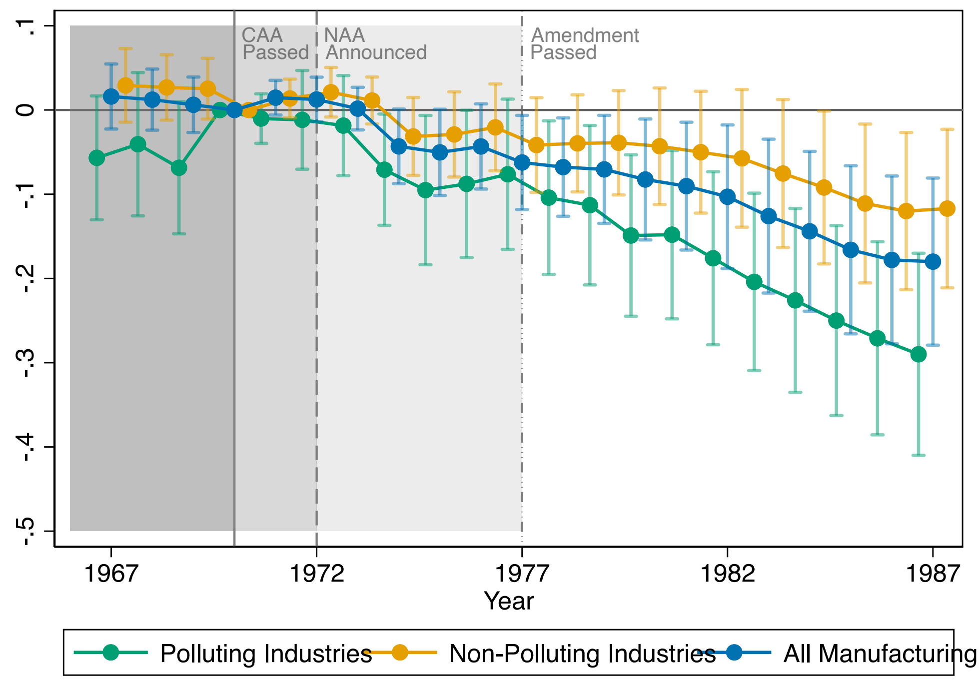


Figure A4: AFS Permit Data

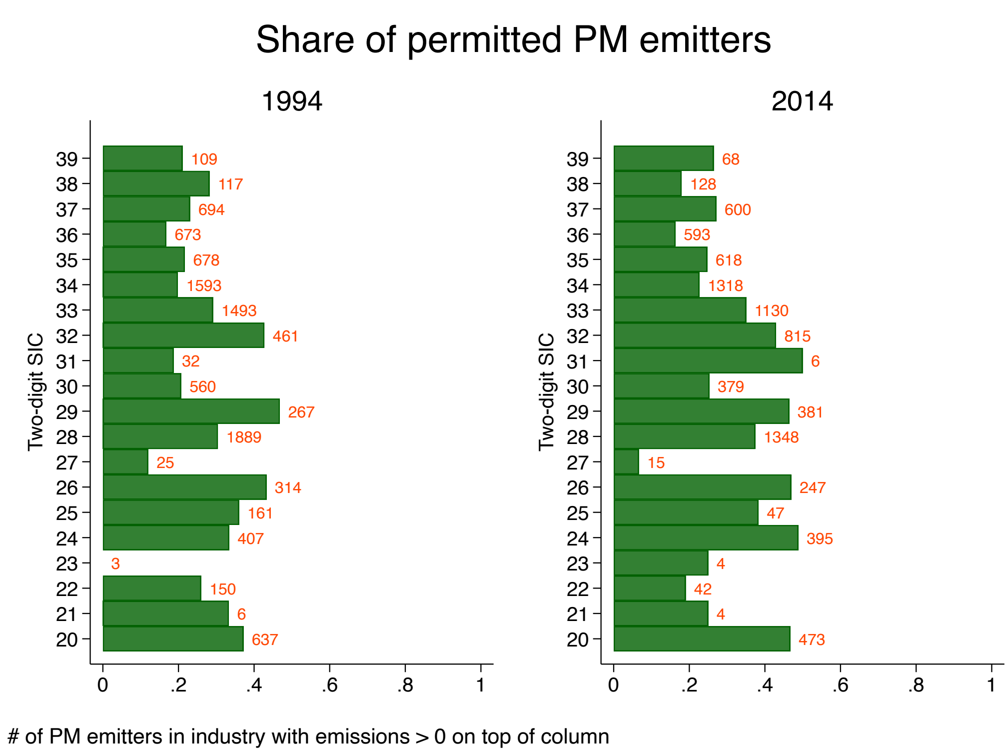


Figure A5: Wage Effects of Nonattainment

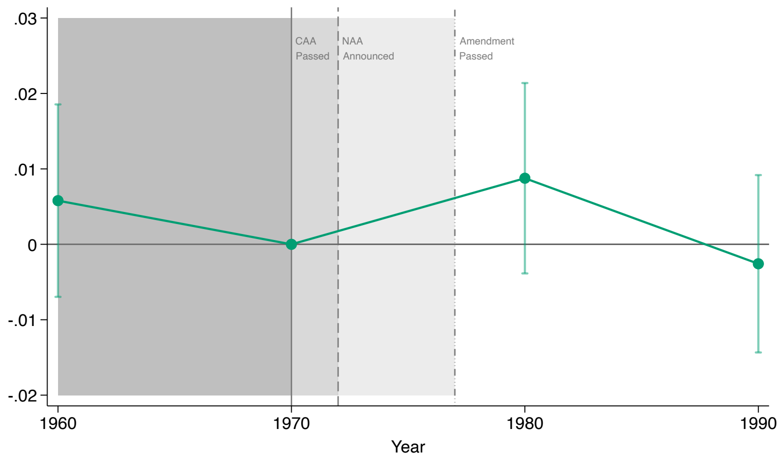
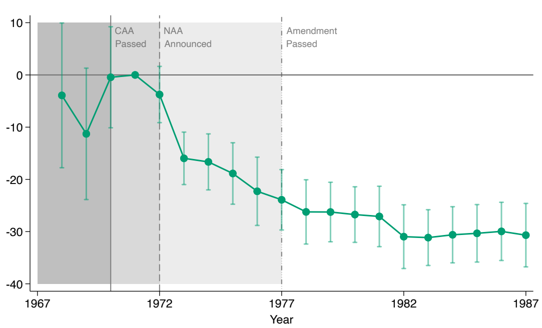
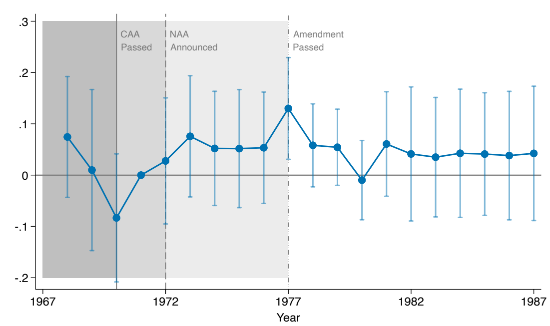


Figure A6: Pollution Effects



(A) Effect of Nonattainment on TSP Pollution



(B) Spatial leakage Effect on TSP Pollution

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)