Size-Based Environmental Regulation: Evidence from Major Clean Air Act Thresholds*

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December 2024

Abstract

Size-based environmental regulation, which applies stricter policy to larger firms, can decrease externalities but also aggregate output by reallocating factors away from large, productive firms. Under the US Clean Air Act, "major source" establishments with predicted pollution emissions above statutory thresholds face stricter regulation. We collect thousands of establishment-level construction permits from the eight states with available records. We find substantial bunching of firm density below major source thresholds, suggesting that these regulations create large compliance costs. Subsequent emissions monitoring helps to validate the bunching estimates. Major sources face half a standard deviation more inspections, fines, and violations. A model of size-based environmental regulation with endogenous pollution abatement provides closed-form equations describing the fixed and variable regulatory costs of major source regulation. We estimate these costs by linking the model to the construction permits and administrative Census microdata. We study how modifying or replacing major source regulation with counterfactual policies affects emissions, output, and social welfare.

JEL Classification: H23, Q50, Q53
Keywords: Bunching, Clean Air Act, environmental regulation, size-based regulation

*We thank Pete Klenow, Emmanuel Saez, Juan Carlos Suarez Serrato, Daniel Xu, participants at the Coase Conference at the University of Chicago and Energy Institute at Haas, and numerous state regulators for useful discussions, Josh Geselowitz, Ian Hardman, Ray Kim, Kenneth Lai, and Calvin Tolbert for outstanding research assistance, and NSF SES-2417375 for generous support. We acknowledge use of Writefull to proofread grammar. Any views expressed are those of the authors and not those of the US Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2211 (CBDRB-FY22-P2211-R9816, CBDRB-FY22-393, CBDRB-FY24-0213)

1 Introduction

Government policy in health care, employment, worker health and safety, and many other domains applies stricter regulation to larger firms. Table 1 describes several prominent environmental and energy policies that apply stricter standards to firms with greater output, capacity, or emissions. Many of the world's most prominent environmental policies incorporate size-based regulation, including the US Clean Water Act, Safe Drinking Water Act, Inflation Reduction Act, the European Union's Emissions Trading System for CO_2, and China's requirement for installation of continuous emissions monitoring systems.

Size-based environmental regulation has benefits and costs. Size-based regulation can help coordinate the targeting of limited enforcement resources. Size-based regulation may reflect political support for policies that favor small firms. Additionally, size-based regulation may provide an efficient policy response to fixed compliance costs (e.g., capital-intensive pollution monitoring equipment). Finally, since power laws describe the distribution of firm size in many settings, regulation targeting large firms may account for a large share of output, employment, and pollution. However, because larger firms generally have greater productivity, size-based regulation can reallocate valuable resources away from productive firms and decrease aggregate output. Thus, the sign and magnitude of size-based environmental regulation's social welfare consequences are unknown.

The US Clean Air Act Amendments provide an important example of size-based environmental regulation. The law designates a new or retrofitted establishment as a "major source" if its "potential to emit" pollution (PTE), a statistic we explain in detail and which represents a plant's maximum possible emissions given its design capacity, exceeds a statutory threshold. A majority of plants face a major source PTE threshold of 100 tons per plant×pollutant×year. Others face thresholds of 10, 25, or 250 tons, and thresholds vary by location, pollutant, and year. Major sources face tighter emissions standards and greater regulatory scrutiny.

We study the effectiveness and efficiency of major source regulation and counterfactual policies, in four steps. First, we quantify bunching around major source thresholds. We collect Clean Air Act construction permits from thousands of establishments in the eight states that maintain PTE records. We link these permits at the establishment level to records of enforcement actions from the US Environmental Protection Agency (EPA); actual pollution emissions from state emissions inventories; and inputs, outputs, and abatement investments from the US Census of Manufactures. Using these data, we analyze patterns of actual emissions, firm density, enforcement actions, and economic outcomes around major source thresholds.

We find substantial bunching of firm density below major source thresholds. This bunching suggests that major source regulation imposes meaningful compliance costs on firms. These compliance costs have sufficiently large magnitude that firms are willing to install additional pollution control equipment, decrease production capacity, or accept other production restrictions to avoid designation as a major source. Firms bunch below major source thresholds partly because major sources face greater regulatory scrutiny. Using principal component analysis, we construct an index of the number of inspections, violations, fines, and other enforcement actions per plant×year. We find that plants above the major source threshold face half a standard deviation more of these enforcement actions than plants below the major source threshold. We also find that PTE strongly predicts ex post actual pollution emissions, which suggests that firms are not avoiding major source regulation through strategic misreporting of PTE, but instead through actual decreases in emissions.

Second, we build a model of size-based regulation and endogenous pollution abatement, which allows ex ante and ex post empirical analysis of specific actual and counterfactual policies. The model weaves together classic ideas from the environmental economics, macro-labor, and macro-trade literatures. In the model, potential entrepreneurs differ in ability and choose how large a firm to create. Producing output also generates pollution, which is taxed, but which firms can decrease by devoting productive resources to abatement. Plants with pollution above a threshold are major sources and must pay a fixed cost and potentially an additional variable pollution tax.

The model provides intuitive closed-form expressions for both the variable and fixed costs of major source regulation in terms of economic objects that we can estimate. Intuitively, the variable cost of major source regulation is proportional to the ratio of the factor shares of labor versus pollution. The fixed cost of major source regulation equals the cost that makes the smallest major source indifferent about whether to remain as a major source or instead restrict emissions and become the largest minor source.

Third, we empirically estimate the fixed and variable costs of major source regulation. Our methodology allows these estimated costs to vary by location and industry. We use several moments to identify and estimate these costs, including the ratio of PTE to actual emissions; the elasticity of emissions with respect to abatement and firm size; and each plant's estimated productivity in the presence of regulation. Using approximations from public data, preliminary estimates find that the average plant in the dirtiest manufacturing industries faces a shadow price of pollution of around \$3,000/ton for particulate matter, \$400/ton for nitrogen oxides, and \$1,800/ton for volatile organic compounds. We compare these magnitudes against mean transaction prices in US air pollution offset markets. Ongoing work on this paper is refining these estimates using administrative census and EPA data,

and obtaining estimates of the fixed cost of major source regulation.

The fourth part of our paper combines the model and data to study how counterfactual policies affect production, pollution emissions, and social welfare. We study five counterfactual policies: removing major source regulation; expanding major source regulation to cover all firms; replacing major source regulation with Pigouvian taxation; choosing the major source threshold which maximizes social welfare; choosing the sizes of the fixed and variable costs of major source regulation which maximize social welfare; and choosing the optimal threshold to declare a source as major. We use a leading integrated assessment model of air quality and valuation, AP3 (Tschofen, Azevedo and Muller, 2019), to estimate the health and welfare consequences of changes in emissions due to a counterfactual.[1] Future work will disclose these counterfactual results from the Census Research Data Center.

We build on three literatures. First, we provide a novel framework to measure the costs of environmental regulation. Future versions of this paper will compare these costs against the health and welfare benefits of regulation due to improved air quality. The framework provides the first model-based analysis of size-based environmental regulation with endogenous pollution abatement. Our general approach may be applicable to other size-based environmental regulations, such as those in Table 1. Existing research measuring the costs of environmental regulation uses engineering estimates, prices of cap-and-trade allowances or pollution offsets, or general equilibrium models (e.g., Hazilla and Kopp 1990; Fowlie, Knittel and Wolfram 2012; Deschenes, Greenstone and Shapiro 2017; Shapiro and Walker 2024).

These existing methods for measuring the costs of environmental regulation have strengths and limitations. For more than half a century, analysts have widely used engineering estimates that sum the capital, operating, and maintenance costs of pollution control equipment, partly due to their wide availability. Engineering estimates, however, may reflect laboratory conditions and are not always close to ex post experimental and quasi-experimental estimates of costs (Carlson et al. 2000; Fowlie, Greenstone and Wolfram 2018; Allcott and Greenstone 2024). Engineering estimates can also miss economic costs of environmental regulation other than end-of-pipe abatement, such as managerial effort, changes in market power and consumer surplus, changes in product quality, and redesign of plant capacity. Prices of cap-and-trade allowances or offsets provide information about marginal abatement costs, although they are available for only the limited number of settings with such markets. They also measure marginal costs of current policy, though they can be more challenging to use for studying counterfactual policy instruments. Our approach has some characteristics

[1] Ongoing work is exploring the use of alternative air quality and valuation models, EASIUR and InMAP (Heo, Adams and Gao, 2016; Tessum, Hill and Marshall, 2017).

in common with research that uses household investments in defenses against externalities, such as asthma inhalers or air filters, to measure the demand for clean air (Deschenes, Greenstone and Shapiro 2017; Ito and Zhang 2020), though we analyze firm defenses rather than household defenses, and we study responses to environmental regulation rather than direct responses to environmental externalities.

This framework for analyzing the costs of environmental regulation can provide useful information for several broader policy debates. Analyzing size-based environmental regulation may provide useful information for governments in many countries that regularly revise environmental policies and choose the scope for size-based regulation, including laws designed to advance the energy transition such as the US Inflation Reduction Act. This analysis can also inform debates about the social welfare consequences of increasingly strict air pollution regulation. Ambient concentrations of many pollutants have fallen more than 90 percent since the 1970 Clean Air Act Amendments, leading to concern about whether air pollution regulation has become more stringent than is optimal (Currie and Walker 2019; Shapiro and Walker 2024). This paper's welfare analysis helps clarify at what point the economic costs of additional regulatory stringency outweigh the environmental benefits. The political popularity and feasibility of size-based environmental regulation makes it a potentially second-best policy in settings where market-based environmental policy instruments are politically infeasible. It can also be valuable to provide policymakers with information on efficiency, cost effectiveness, optimal design, and other attributes of politically feasible but second-best environmental policy instruments (Goulder 2020).

Second, we contribute to the bunching literature from public and labor economics (Saez 2010; Chetty et al. 2011; Kleven and Waseem 2013; Kleven 2016; Bachas and Soto 2021). Our setting differs in several dimensions from most of this work. Because we do not observe the ad valorem tax rate that regulated agents face, we must estimate both the implicit tax rates that regulation creates and the effects of these implicit taxes. This explains why our paper relies more on model structure than most bunching papers do. Unusually, our setting provides ex post data on actual pollution emissions to clarify whether bunching reflects strategic misreporting or true changes in firm behavior. Askenazy, Breda and Pecheu (2022), for example, argue with independent measures of firm size that the much-studied bunching of French firms around a regulatory threshold of 50 workers is only an accounting manipulation. Finally, while many papers observe bunching in their major economic outcomes of interest (e.g., worker income, government tax receipts, or worker employment), we observe bunching in PTE and must infer its implications for other outcomes of interest, including the economic costs of regulation. We believe that most size-based environmental policies, like those in Table 1, share these features of our setting and therefore differ from most existing bunching

settings.

Our model builds on Garicano, Lelarge and Reenen (2016), using ideas from Lucas (1978) and Melitz (2003), and weaving in a version of the abatement technology from Copeland and Taylor (1994, 2003) that other work applies empirically (Shapiro and Walker 2018; Duan et al. 2021; Egger, Kreickemeier and Richter 2021; Qi, Tang and Xi 2021). None of this work studies size-based environmental regulation. Ghanem and Zhang (2014) and Ito and Sallee (2018) observe bunching around fuel economy thresholds and solar installation cutoffs, though few environmental papers directly analyze bunching, and we are not aware of any bunching-based analysis of the major environmental regulations in Table 1. Chen et al. (2021) study energy regulation for large firms in China, though do not focus on firms' strategic bunching behaviors. Fenske, Haseeb and Kala (2023) analyze environmental permits in India, though not bunching.

Third, we provide the first detailed analysis of the US Clean Air Act's major source thresholds, and the first analysis of PTE microdata in academia, government, the private sector, or any other source. Much environmental economics research studies how Clean Air Act regulation affects firm profits, employment, worker earnings, productivity, and abatement expenditures (Becker and Henderson 2000; Greenstone 2002; Keller and Levinson 2002; List, McHone and Millimet 2004, 2005; Hanna 2010; Greenstone, List and Syverson 2012; Walker 2013; Shapiro and Walker 2018; Aldy et al. 2022). Shapiro and Walker (2024) study prices and quantities in Clean Air Act offset markets to learn about marginal abatement costs. Many papers mention that plants with PTE above 100 tons in nonattainment areas face major source regulation (Becker and Henderson 2000; List, McHone and Millimet 2004, 2005; Walker 2011; Greenstone, List and Syverson 2012; Lim 2016), though do not elaborate on this observation. As we explain, major source thresholds are not always 100 tons. While the PTE microdata are central to our analysis, prior work has not analyzed them because they require substantial time and effort to obtain, interpret, and harmonize across states, and because regulators and regulatory databases focus on whether an establishment is a major source but not on its PTE.

The rest of the paper proceeds as follows. Section 2 provides background. Section 3 describes the data. Section 4 characterizes patterns of outcomes around major source thresholds. Section 5 explains the model. Section 6 discusses model-based estimates of the fixed and variable costs of major source regulation and the impacts of counterfactual policies. Section 7 concludes.

2 Institutional Background

The 1970 Clean Air Act Amendments (CAA) provide the cornerstone of US air pollution regulation. The CAA requires large stationary pollution sources to face stricter environmental regulation. Stationary sources include factories and utilities but exclude transportation. Areas with ambient air pollution exceeding national air quality standards are declared to be in nonattainment for a pollutant and face additional regulations, including tighter major source standards. The severity of nonattainment ("extreme," "marginal," etc.) and the associated stringency of regulation depend on the severity of a region's air pollution.

Regulators specify a PTE threshold, and plants with PTE exceeding this threshold are major sources. Areas in attainment have a major source threshold of 250 tons per year for most industries, most nonattainment areas have a major source threshold of 100 tons per year, areas in severe nonattainment have a major source threshold of 25 tons per year, and the South Coast air quality region around Los Angeles has a major source threshold of 10 tons per year. These standards apply separately to each pollutant for an establishment, so a plant with PTE of 99 for two different pollutants is a minor (nonmajor) source, while a plant with PTE of 101 for one pollutant is major.

To calculate PTE and determine which sources are major, the CAA requires stationary pollution sources to obtain a permit.[2] The EPA defines PTE as, "The maximum capacity of a stationary source to emit under its physical and operational design," considering abatement equipment, operating hours restrictions, or types of materials, as enforceable by the EPA (Seitz and Schaeffer 1998). Thus, a permit specifies the maximum hours per week the plant may operate, the production and abatement technology the plant uses, etc. Regulators typically write a permit when a plant is built, renew the permit on regular cycles, and revise it when a plant has substantial retrofits. The permit sums PTE across units within a plant.

The EPA condones modifications of plant design to avoid major source regulation. Regulators and engineering consultants carefully measure PTE and document the measurement in permits that can fill dozens of pages. Policy formalizes methods for calculating PTE. Some plants would have been major sources, but restrict their permitted hours of operation, decrease production capacity, or expand pollution controls specifically to avoid major source regulation. The EPA designates such sources as "synthetic minors" and gives extra scrutiny to their PTE calculations.[3]

[2]For major sources only, the Clean Air Act calls these "operating permits." Some states refer to the initial stage in this process as obtaining a "construction permit." We generally refer to these as construction permits.

[3]Formally, a synthetic minor plant would typically have PTE above the major source threshold given its capacity and production design, but the plant has adopted enforceable restrictions on production or emissions which make its PTE below the threshold.

Major source standards apply to a variety of pollutants. We focus on five of the six "criteria pollutants" the CAA regulates. Major source designations for nitrogen oxides (NO_x) and volatile organic compounds (VOCs) are common, since they contribute to ground-level ozone, which is a widespread problem nationally, and since many plants emit these pollutants through both combustion and material processing. Major source declarations for particulate matter are also common. Major source declarations for carbon monoxide and sulfur dioxide are less common. We do not analyze major source declarations for lead, which is no longer a primary focus of changing regulation for most US industrial plants. We abstract from major source declarations under the "hazardous" or "toxic" pollutants the EPA designates, since they are less standardized and have less easily available data.

Designating an establishment as a "major source" triggers many additional regulations. The pollution standard for major sources in nonattainment areas, the Lowest Achievable Emissions Rate (LAER), requires a new or retrofitted source to have the emission rate of the cleanest source anywhere using similar production technology, regardless of the costs. Minor sources face weaker emissions standards which may consider costs, such as Reasonably Available Control Technology (RACT). Major sources also face more frequent inspections, larger fines, and other regulatory scrutiny.

3 Data

The critical and novel data for this paper describe the PTE of each new or retrofitted plant, which we obtain from the text of construction permits in each US state with available data. For each state, we sought these records through contacting state regulators and filing state Freedom of Information Act and associated (e.g., open record or Sunshine Law) requests. We focused effort on states with the largest number of major sources, as listed in the EPA's Air Facility System or National Emissions Inventory. Obtaining and interpreting PTE data for most states has required repeated and detailed conversations with state regulators.

Appendix Figure A1 shows one table from an example permit. This permit describes the Lynch gas-fired power plant in North Little Rock, Arkansas. The yellow boxes show the two pieces of information that we extract. The "pollutant" column lists the pollutants for which we extract information. The "tpy" column shows the short tons of pollution emissions per year, which represent PTE. This plant is a major source for three pollutants: sulfur dioxide (SO_2), carbon monoxide (CO), and nitrogen oxides (NO_x), since annual emissions of each exceed 100 tons.[4]

Table 2 describes the PTE data we have obtained from eight states: Illinois, Kentucky,

[4]This plant was decommissioned in the 2010s, part-way through our sample period.

Louisiana, Minnesota, New Mexico, Nevada, North Carolina, and Washington.[5] Illinois represents an outsized share of the data, as it has the most complete records.[6] Many of the other states we contacted indicated that they do not keep PTE records and only maintain records of whether a plant is major. Our analysis sample includes 417,000 observations from 37,000 plants, so the mean plant has 11 observations (typically representing several pollutants and years). The data cover the last 35 years, with nearly half of the observations from the 2010s. About 84 percent of observations have a major source threshold of 100 short tons, while 16 percent of observations have a threshold of 25 tons. Ongoing work for this paper is setting up data on plants with major source thresholds of 10 and 250 tons.

PTE data format varies by state. Most states store permits in thousands of PDF files, many using disparate permit formats even within a state. To extract PTE and plant identification information, we use automated software where feasible and accurate and we use manual entry for data formats where automated software was infeasible or inaccurate. We carefully check the accuracy of automated and manual data entry. Some states have each unit within a plant report PTE separately. In these cases, we sum across units to obtain plant-level PTE and confirm with state regulators that this summation matches their practice. Some states provide permits for each plant in each year, others in a current year, and others provide permits only in the year a plant is built. Ongoing work for this paper is documenting and harmonizing these differences across states. The PTE data typically include major sources, minor sources, and synthetic minor sources.

For each state, where possible, we also obtain plant×year emissions from state emissions inventories. These inventories are the basis for the EPA's National Emissions Inventory, which much economic research analyzes (Levinson 2009; Muller, Mendelsohn and Nordhaus 2011; Holland et al. 2016; Blundell, Gowrisankaran and Langer 2020; Zou 2021).

We obtain records of compliance and enforcement actions by plant×year from the EPA's Enforcement and Compliance History Online (ECHO) database. Additionally, we obtain additional identifying information for each establishment, such as address, industry, and name, from the EPA's Facility Registration System (FRS), which helps join datasets at the establishment level.

We link these establishment records to restricted access Census administrative microdata, which we access through the Census Research Data Centers, in a few steps. From each

[5]Washington State, like California, regulates pollution through regional clean air districts; only the Southwest district in Washington could provide PTE. Ongoing work on this project is adding data from Arkansas and from California (San Joaquin air district)

[6]Illinois has a major source standard of 100 tons for most plants, but for NO_x and VOCs, it applies additional regulatory scrutiny and collects some fees from plants with PTE above 25. This leads to some bunching at both 25 and 100 for these plants. This manuscript excludes these plants from analysis restricted to plants with a 100 ton threshold, although ongoing work is accounting for them in alternate ways.

permit, we extract all the identifying information available for the plant, including the name of the firm and the establishment, the address, geographic coordinates, and the industry code. For some states, the unique plant identification code in the PTE data appears in the FRS, which provides additional plant identification variables. We then match each plant to the corresponding establishment in the Census administrative microdata. This match requires a series of probabilistic links and then repeated checks to ensure accuracy. Our previous research has completed versions of this matching (Walker 2013; Shapiro and Walker 2018). We prioritize accurate matches over sample size, so we exclude plants where this method does not give high confidence in a match between public and administrative Census data.

We analyze several administrative Census databases. The Pollution Abatement Cost and Expenditures (PACE) survey reports abatement capital and operating expenditures for a large sample of plants. Data are available for survey years 1990 and 2005, although the two are not comparable for use as a panel. From the Census of Manufactures, we observe plant-level revenues, value added, material expenditures, employment, and worker earnings. Because these variables are not available for other sectors, much of our analysis is restricted to manufacturing. We calculate the plant's wage as worker earnings divided by employment. We calculate costs as revenues minus value added minus material expenditures. We calculate the share of costs devoted to abatement as abatement expenditures divided by costs.

4 Outcomes Around Major Source Thresholds

This section describes patterns of firm outcomes around major source thresholds. We discuss three sets of outcomes: plant density, pollution emissions, and compliance actions. Ongoing work is calculating similar results for variables in the Census microdata, including revenues, costs, productivity, and abatement.

4.1 Firm Density Around Major Source Thresholds

Figure 1 plots firm density around major source thresholds. Panel (a) includes only plants facing a PTE threshold of 25. Panel (b) includes only plants facing a PTE threshold of 100. Panel (c) pools the two thresholds and shows a range of 20 tons on either side of the threshold. We limit the sample to observations with major source thresholds of 25 or 100, since these are the thresholds for which we have data currently setup. Each underlying observation represents a plant×pollutant×year. For example, one observation might represent the PTE of a specific power plant's emissions of nitrogen oxides in the year 2005. The analysis gives equal weight to each plant, so that a plant with six observations (e.g., three pollutants, each

reported in two separate years) has one-sixth the weight per observation as a plant with one observation. The horizontal axis in panels (a) and (b) shows PTE in short tons. The horizontal axis in panel (c) shows PTE minus the applicable major source threshold. For example, an observation at 10 on the horizontal axis of panel (c) has PTE exceeding the applicable major source threshold by ten tons. We divide plants into sixteen equal-sized bins based on their x-axis value. The height of each bar shows the (weighted) share of observations from each bin.

Figure 1 reveals enormous bunching around major source thresholds. Panel (a) shows that plants facing a threshold of 25 tons have excess mass below 25 tons, although they do not have substantially excess mass just below 100 tons. Panel (b) shows that plants facing a threshold of 100 tons have excess mass below 100 tons, although they do not have substantially excess mass just below 25 tons. In both cases, plants bunch below the relevant threshold. Panel (c) summarizes that the data show a substantial drop in density precisely at the threshold. Many plants have PTE below the threshold; fewer plants have PTE above the threshold. Plants bunch below the threshold to avoid major source regulations. This bunching, which previous analysis has not documented, provides this paper's first main finding. This bunching suggests that major source regulations impose substantial costs on firms. These costs have a sufficient magnitude that firms undertake costly responses to avoid major-source regulation. Additionally, Figure 1 shows several other important aspects of firm bunching, which motivate various aspects of the model that the latter parts of our paper analyze. Figure 1 shows precise bunching. The bin immediately to the left of the major source threshold shows the greatest mass. The size of this bin suggests that some firms choose PTE precisely to avoid major source regulation. Figure 1 also shows imprecise bunching– most bins below the threshold show excess mass, while most bins above the threshold show a deficit of mass. This contrasts with many bunching papers, which find only a bulge just below the threshold and a trough just above it.

Figure 1 also shows that bunching has large magnitude. Bins below the major source threshold have more than twice the density of bins to the right of the threshold, suggesting that many firms avoid major source regulation through imprecise bunching. The decrease in firm density above the threshold extends at least 20 tons above the threshold.

4.2 Actual Pollution Emissions Around Major Source Thresholds

Although regulators carefully measure PTE to prevent strategic misreporting by firms, in theory firms could strategically manipulate PTE without changing actual emissions. As a check on the accuracy of the PTE data, we compare PTE to actual emissions data, measured

after a plant is built, as recorded in state inventories. PTE reflects a prediction of the maximum pollution a plant could emit given its design and permit, and is calculated when a plant is built; actual emissions are subsequent estimates of the pollution a plant emits.

A plant's PTE should substantially exceed its actual emissions, since PTE represents the maximum a plant could potentially emit. Actual emissions also have their own sources of measurement error, as plants could under-report true emissions, not all actual emissions come from the highest-quality methods (continuous emissions monitoring systems), and other research documents measurement error in actual emissions data (de Marchi and Hamilton, 2006). Our main question is whether the relationship between actual emissions and PTE varies near the major source threshold. If plants understate PTE to avoid being major sources, but do not change their actual emissions, then data would show a higher ratio of actual emissions to PTE for minor sources, especially near the major source threshold.

To study this relationship, we estimate a binned scatter plot, adjusted by fixed effects:

$$e_{ict} = \sum_{b'} \gamma_{b'} 1[b_{ict} = b'] + \mu_c + \pi_{st} + \varepsilon_{ict} \tag{1}$$

Here e_{ict} represents the actual emissions of plant i for pollutant (chemical) c in year t, as recorded in state emissions inventories. The main explanatory variables, $1[b_{ict} = b']$, represent indicators for whether $(\mathcal{P}_{ict} - M_{ict})$, the difference between PTE $\mathcal{P}$ and the major source threshold M for observation (i, c, t), is in one of ten bins. For example, an observation in the first bin ($b_{ict} = 1$) has PTE that is sixteen to twenty tons below the major source threshold ($-20 \leq \mathcal{P}_{ict} - M_{ict} \leq -16$). The regression controls for pollutant fixed effects μ_c and state-by-year fixed effects π_{st}. These fixed effects decrease variance, including from any state-specific data idiosyncracies, and compare within pollutant and within state×year. The regression weights each plant equally. As discussed earlier, one plant can have multiple observations due to emitting multiple pollutants or having operating permits for multiple years. To facilitate the interpretation of the vertical axis, we plot the sum of the bin fixed effects $\gamma_{b'}$ and the overall sample mean emission rate $\sum_{i,p,t} e_{ipt}/N$, where N represents the total number of observations.

Figure 2 shows estimates of the $\gamma_{b'}$ coefficients from equation (1) against the bin they represent. The vertical axis shows actual pollution emissions in short tons. The horizontal axis shows PTE minus the relevant major source threshold. The circles in the graph depict the actual pollution that the mean observation in each bin emits. The red line shows the linear trend.

Figure 2 suggests that the relationship of actual emissions to PTE is similar for major and minor sources. The upward slope of these points and the red line indicates that plants

with greater PTE have greater actual pollution emissions. The points' slope is somewhat though not perfectly linear. If plants strategically under-report PTE in order to be classified as a minor source, but then emit large amounts of actual pollution after construction, then this graph would show a higher ratio of actual pollution to PTE for minor than for major sources. Figure 2 shows no evidence of such behavior. Most points lie near the linear trend, indicating a near-constant ratio of actual emissions to PTE.

Figure 3 transforms these data to show how the ratio of pollution emissions to PTE changes with PTE. This figure reports a version of equation (1) where the dependent variable represents the ratio of emissions to PTE, $e_{ips}/\mathcal{P}_{ips}$. The ratio on the vertical axis of this figure is far below one because PTE represents a plant's maximum potential pollution emissions, assuming the plant operates at maximum capacity for all permitted hours. Most points have a ratio near 0.20. This ratio would be consistent, for example, with a plant certified to operate at all hours, but that only actually operates 7.5 hours per weekday, with 4 weeks per year of maintenance ($\approx (7.5 \cdot 5 \cdot 48)/(24 \cdot 365)$). This ratio of approximately 0.2 provides one parameter of the model that subsequent sections of this paper analyze.

The points in Figure 3 have sufficient variance that the ratio of emissions to PTE for major sources may be 1 to 2 percent less than for non-major sources, though this pattern is not completely clear. Such a decrease would be consistent with a scenario where the additional inspections and compliance actions that major sources face modestly decrease their emissions relative to PTE.

4.3 Compliance Actions Around Major Source Thresholds

Figure 4 shows how environmental compliance and enforcement vary around major source thresholds. As in the earlier figures, the horizontal axis shows PTE minus the major source threshold the plant faces, divided into ten equal-sized bins. Each blue circle shows the mean value for observations in one bin. The vertical axis plots an index of regulatory enforcement constructed with principal component analysis across the eight measures of compliance actions that we can observe in EPA records—compliance evaluations; stack tests; certifications; formal actions; informal actions; penalties; high priority violations; and federally-reportable violations. The index has mean zero and standard deviation one, so it can be interpreted as z scores of regulatory enforcement.

Figure 4 shows that major sources face more compliance actions. The discrete increase in inspections occurs precisely at the major source threshold and persists throughout the 20-ton range on either side of the threshold. Away from the threshold, data show a somewhat flat relationship between inspections and PTE. Figure 4 suggests that major sources face half a

standard deviation greater regulatory enforcement than minor sources. This is qualitatively consistent with the objective of the Clean Air Act, which imposes stricter regulation on major sources. It also explains why firm density shows bunching below major source thresholds, since enforcement actions like inspections and fines increase firm costs, which some firms prefer to avoid by decreasing their PTE.

Appendix Figure A2 shows patterns for the eight compliance and enforcement measures separately. The graph shows a standardized version of each variable. One of the eight, low priority violations, shows little variation, and no clear difference between major and minor sources. Another two, informal actions and the log penalty amount, shows a noisy but perhaps moderate increase for major sources. The other five measures show large and visually clear increases for major versus minor sources—compliance evaluations, certifications, formal actions, formal actions with a penalty, and high priority violations.

The enforcement actions described in Appendix Figure A2 provide an imperfect measure of regulation. For example, they do not measure the additional spending on abatement, monitoring, or compliance a firm may have to support (including offset credits, as in Shapiro and Walker (2024)), they do not measure the severity of each type of action, they miss qualitative or informal communication between firms and regulators, and they miss public attention due to enforcement which may affect a firm's reputation. These data primarily include federal enforcement actions, and local regulators may base their own enforcement actions on a plant's status as a major source. Additionally, we lack a simple, model-free methodology to transform these compliance actions into a fixed or variable shadow price of regulation.

For these reasons, we do not use these enforcement data to estimate model parameters. Instead, we take them as direct evidence that major source regulation creates real compliance costs, and subsequent sections of this paper use other methods to estimate the dollar value of these costs.

4.4 Economic Outcomes Around Major Source Thresholds

Ongoing work for this paper is estimating figures like Figure 4, but where the y-axis shows revenues, costs, abatement expenditure, or total factor productivity. We will add these to the draft once they are disclosed from the Census Research Data Center.

4.5 Synopsis of Bunching Results

Many bunching papers observe the tax rate that firms or households above a size threshold face, estimate the excess mass below the threshold, and then estimate the elasticity of density

with respect to the tax rate. In our setting, no ad valorem data exist on the full costs of Clean Air Act major source regulation. Hence, we seek to estimate both the fixed and variable costs of being a major source and to estimate how major source regulations change the distributions of environmental and economic outcomes.

We thus turn to a model of bunching with endogenous pollution abatement. This model makes strong assumptions. Although the assumptions do not provide a literal description of every firm's behavior, they do capture important features of regulation. They also provide a way to use the data described in this section to learn about the economic costs, environmental benefits, and social welfare impacts of major source regulation and counterfactual policies.

5 Model of Size-Based Environmental Regulation

This section describes our model of size-based environmental regulation and endogenous pollution abatement; Appendix C provides additional results. This model has several purposes– to help interpret the empirical patterns that the previous section documents; to provide a methodology to estimate the fixed and variable costs of major source regulation; and to study effects of counterfactual policies.

We proceed in six steps. First, we present the model assumptions. Second, we find a plant's optimal choices. Third, we describe the density and distribution of PTE across plants. Fourth, we account for measurement error in PTE. Fifth, we describe closed-form equations for fixed and variable costs of major source pollution regulation. Sixth, we explain methodology to assess how counterfactual policies affect emissions, output, and social welfare.

5.1 Model Assumptions

This subsection describes the basic model assumptions. An economy has a population of entrepreneurs. An entrepreneur has the ability α and may choose to form a firm. Each entrepreneur has a unique blueprint, and firms engage in monopolistic competition. The distribution of ability across entrepreneurs follows a power-law distribution with parameters c_α and β_α:

$$\phi(\alpha) = c_\alpha \alpha^{-\beta_\alpha} \tag{2}$$

Entrepreneurs who choose not to form a firm work as employees at the wage w. We assume that talent is sufficiently scarce that $\alpha\phi(\alpha)$ is decreasing in α.

Production generates two types of output. A firm produces

$$q = \kappa_q(1-a)\alpha n \tag{3}$$

units of goods, sold at the price p. Production uses n workers and allocates a share $a \in [0,1]$ of potential output to abating pollution. The constant κ_q describes output of a firm with no abatement, with productivity $\alpha = 1$, and with one worker. This constant allows us to separate the mean productivity κ_q from the plant-specific productivity α, a property that we use later in estimation. Equation (3) shows that abatement decreases output but that we can separate productivity α, which we assume is fixed for a firm, from abatement a, which the firm chooses.

Firms also produce pollution emissions e, using the following technology:

$$e = \kappa_e(1-a)^{1/\beta}\alpha n \tag{4}$$

Emissions in (4) equal a function of employment n, ability α, and the abatement share a, scaled by the pollution elasticity β. The mean emissions κ_e of a plant with no abatement, with productivity $\alpha = 1$, and with one worker allow emissions to have different units than output, which is also useful later in applying the model empirically. Equation (4) shows that we can interpret β as the inverse elasticity of emissions with respect to the share of non-abatement investments, so we sometimes refer to β as the pollution elasticity. All else equal, increasing the pollution elasticity β increases a plant's pollution emissions.

Combining equations (3) and (4) implies that the firm's output q is a Cobb-Douglas function of emissions and workers:

$$q = \kappa_q \kappa_e^{-\beta} \alpha^{1-\beta} e^{\beta} n^{1-\beta} \tag{5}$$

Because Cobb-Douglas production implies constant budget shares, equation (5) implies that β also represents the cost share of pollution in production, a property that Section 5.5 uses to recover the shadow price of pollution for firms.

A firm with PTE above the major source threshold ($\mathcal{P} > \overline{\mathcal{P}}$) faces a fixed cost F and a variable cost of PTE, τ_1. A firm with PTE weakly below the threshold ($\mathcal{P} \leq \overline{\mathcal{P}}$) faces a lower variable cost of PTE, $\tau_0 \leq \tau_1$. These terms (F, τ_0, τ_1) summarize the regulatory cost of Clean Air Act major source thresholds, and these regulatory costs explain why firms invest in abatement. Section 5.5 describes how we estimate them.

A firm chooses prices p and abatement a to maximize profits:

$$\pi(\alpha) = max_{p,a} p(1-a)\alpha n - wn - \tau\mathcal{P} - F \cdot 1[\mathcal{P} > \overline{\mathcal{P}}] \tag{6}$$

We use the shorthand $\tau \equiv \tau_0 1[\mathcal{P} \leq \overline{\mathcal{P}}] + \tau_1 1[\mathcal{P} > \overline{\mathcal{P}}]$, where $1[\cdot]$ represents the index function. Reflecting Figure 3, we assume that the ratio of PTE to actual emissions equals a constant ρ:

$$\mathcal{P} = \rho e \tag{7}$$

Consumers have isoelastic demand:

$$q = p^{-\sigma} \tag{8}$$

When applying this model with data, we explore allowing σ and other parameters to vary by industry.

A few comments clarify the roles of pollution and abatement in these assumptions. Pollution could appear a few different ways in a firm's problem—a firm might treat pollution as an output on which it is taxed, as above; or a firm might use the ability to emit pollution as a productive input; or a firm might face a regulatory constraint on its pollution intensity. The formulation above has the advantage that it accommodates these explanations and makes them analytically equivalent (Copeland and Taylor 2003).

5.2 Plant Optimization

This subsection derives a plant's optimal choices. Rearranging the first-order condition of profits (6) for prices at an interior solution gives

$$p = \frac{\sigma}{\sigma - 1} \frac{1}{1-a} \left(\frac{w}{\alpha} + \tau\rho(1-a)^{\frac{1}{\beta}} \right) \tag{9}$$

Here the firm has a markup of $\sigma/(\sigma-1)$, which follows from our assumption of monopolistic competition. The remainder of the right-hand side of equation (9) describes the firm's marginal cost. We can equivalently and perhaps more intuitively write marginal cost as the marginal demand for labor times its price, plus the marginal demand for pollution times its price, $w\frac{dn}{dq} + \tau\frac{d\mathcal{P}}{dq}$. Of course, the firm also chooses the abatement share a in equation (6).

The first-order condition for pollution abatement at an interior solution of equation (6)

also shows sensible patterns:

$$a^* = 1 - \left[\frac{1}{\tau\rho}\frac{\beta}{1-\beta}\left(\frac{w}{\alpha}\right)\right]^{\beta} \tag{10}$$

Equation (10) shows that increasing variable pollution taxes τ increases the share of investment in abatement a^*. Additionally, conditional on regulation and other forces in the model, plants with greater productivity α invest a larger share of costs on abatement, which echoes the common finding that more productive plants have lower emission rates (Bloom et al. 2010; Shapiro and Walker 2018; Klenow, Pasten and Ruane 2024). In our model, the reason for this comparative static is that plants with greater productivity have lower marginal costs. As rising productivity decreases their prices, a plant receives less revenue from each unit sold, but must pay the same tax on each unit of pollution emitted, which therefore makes pollution relatively more costly to emit, and encourages abatement.

Combining the first-order conditions for pricing and abatement (9) and (10) yields a standard pricing equation:

$$p^* = \frac{\sigma}{\sigma-1}\frac{\rho^{\beta}}{\alpha^{1-\beta}}\frac{\kappa_e^{\beta}\tau^{\beta}w^{1-\beta}}{\beta^{\beta}(1-\beta)^{1-\beta}}\frac{1}{\kappa_q} \tag{11}$$

Equation (11) again shows that price is a constant markup $\sigma/(\sigma-1)$ over marginal cost. The form of marginal cost reflects the Cobb-Douglas structure in (5). Marginal cost is a simple function of exogenous variables—pollution taxes, wages, the pollution elasticity, the ratio of PTE to emissions, and plant productivity ($\tau, w, \beta, \rho, \alpha$).

These first-order conditions also imply sensible plant choices of emissions and employment:

$$e^* = \left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\left(\frac{w}{\alpha(1-\beta)}\right)^{(1-\beta)(1-\sigma)}\left(\frac{\beta}{\tau\rho\kappa_e}\right)^{1-\beta(1-\sigma)}\left(\frac{1}{\kappa_q}\right)^{1-\sigma} \tag{12}$$

$$n^* = \left(\frac{\sigma}{\sigma-1}\frac{1}{\kappa_q}\right)^{-\sigma}\left(\frac{w}{\alpha(1-\beta)}\right)^{-\beta(1-\sigma)-\sigma}\left(\frac{\beta}{\tau\rho\kappa_e}\right)^{-\beta(1-\sigma)}\frac{1}{\alpha\kappa_q} \tag{13}$$

$$\mathcal{P}^* = \rho e^* \tag{14}$$

All else equal, plants facing stricter regulation τ emit less pollution; plants with greater productivity α have higher pollution emissions and PTE.

This subsection derives results for plants at an interior optimum $\mathcal{P} \neq \overline{\mathcal{P}}$, which are not bunching at the threshold. Appendix equations (C–1) through (C–3) show corresponding results for firms that bunch at the major source threshold, so have $\mathcal{P} = \overline{\mathcal{P}}$.

5.3 Model Distributions

This subsection describes the distribution and density of pollution and productivity across plants. Let α_{min} describe the productivity of the lowest-productivity entrepreneur who chooses to form a plant rather than work for wages. Let $z \equiv \mathbb{P}(\alpha \geq \alpha_{min})$ equal the share of entrepreneurs who form a firm. We can write the cumulative distribution of PTE as

$$X(\mathcal{P}) = \frac{1}{z} \int_{\alpha_{min}}^{\alpha(\mathcal{P})} \phi(b) db \tag{15}$$

where $\phi(\cdot)$ is the density of ability from equation (2). Differentiating, applying Leibniz integration rule, and substituting in each plant's PTE from (14) yields the density of PTE:

$$\chi(\mathcal{P}) = \frac{\phi(\alpha(\mathcal{P}))}{z} \left[\frac{1}{\rho} \left(\frac{\sigma}{\sigma - 1} \right)^{\sigma} \left(\frac{\tau \rho \kappa_e}{\beta} \right)^{1-\beta(1-\sigma)} \kappa_q^{1-\sigma} \right]^{\frac{1}{(\beta-1)(1-\sigma)}} \frac{w}{1-\beta} \frac{\mathcal{P}^{\frac{1}{(\beta-1)(1-\sigma)}-1}}{(\beta-1)(1-\sigma)} \tag{16}$$

Section 5.6 uses the density and distribution of PTE from (15) and (16) to assess how counterfactual policies affect emissions and output.

The conditional density of PTE clarifies patterns for each group of firms and helps connect the theory and data in the next subsection. Entrepreneurs sort into several groups based on ability. Entrepreneurs with ability strictly below α_{min} become workers. Entrepreneurs with ability in the range $[\alpha_{min}, \overline{\alpha})$ become minor sources. Entrepreneurs with ability in $(\overline{\alpha}, \alpha_r)$ bunch at the major source threshold, so emit $\overline{\mathcal{P}}$. Finally, entrepreneurs with ability $\alpha \geq \alpha_r$ become major sources.

A free entry condition and the fact that a density integrates to one provide simple descriptions of the ability and PTE of the smallest firm $(\alpha_{min}, \mathcal{P}_{min})$; Appendix C provides details. These results let us parsimoniously describe the conditional density of PTE for each of these groups of firms:

$$\chi^*(\mathcal{P}) = \begin{cases} -\gamma \frac{\mathcal{P}^{\gamma-1}}{\left[\mathcal{P}_{min}^{\gamma} - T\mathcal{P}_{max}^{\gamma}\right]} & \text{if } \mathcal{P}_{min} \leq \mathcal{P} < \overline{\mathcal{P}} \\ \frac{\left[(\overline{\mathcal{P}})^{\gamma} - T(\mathcal{P}_r)^{\gamma}\right]}{\left[\mathcal{P}_{min}^{\gamma} - \mathcal{T}\mathcal{P}_{max}^{\gamma}\right]} & \text{if } \mathcal{P} = \overline{\mathcal{P}} \\ 0 & \text{if } \overline{\mathcal{P}} < \mathcal{P} < \mathcal{P}_r \\ -\gamma \frac{T\mathcal{P}^{\gamma-1}}{\left[\mathcal{P}_{min}^{\gamma} - T\mathcal{P}_{max}^{\gamma}\right]} & \text{if } \mathcal{P}_r \leq \mathcal{P} \end{cases} \tag{17}$$

where γ equals a constant function of model parameters, defined in Appendix equation (C–6). Here $\mathcal{P}_{max}$ is the PTE of the largest firm.

Figure 5, panel (a), shows a graphical analogue equation (17). The y-axis describes firm

density and the x-axis describes PTE. The smallest firm has PTE of $\mathcal{P}_{min}$, and the density for minor sources follows a power law distribution, as in the first case in equation (17). A discrete increase in density appears for firms with PTE of $\overline{\mathcal{P}}$, corresponding to the second case of equation (17). As the third case of equation (17) shows, no firms have PTE in the range $(\overline{\mathcal{P}}, \mathcal{P}_r)$, since all these firms instead decreased their PTE to $\overline{\mathcal{P}}$ to avoid being major sources. Reflecting the fourth case of equation (17), the density of major sources follows a smooth power law distribution. The fixed and variable regulatory costs of major source regulation (F, τ_1) account for the zero density in the range $(\overline{\mathcal{P}}, \mathcal{P}_r)$, the discretely lower density above $\mathcal{P}_r$, and possibly different slope of the density among major sources.

5.4 Empirical Model

This subsection accounts for measreuement error in PTE and derives a likelihood function that we use to estimate several parameters. A few features of the conditional density in (17) do not match the empirical distribution of PTE that our microdata show. The conditional density for $[\mathcal{P}_{min}, \overline{\mathcal{P}})$ in (17) shows no excess mass modestly below the threshold. The conditional density for $\mathcal{P} = \overline{\mathcal{P}}$ shows that all the excess mass due to bunching appears precisely at the threshold. The conditional density for $(\overline{\mathcal{P}}, \mathcal{P}_r$ indicates that no plants have a density just above the threshold. None of these accurately describes true patterns in the PTE microdata.

To relax these results, we assume that the PTE reported in data, used for assignment to major source regulation, and for pollution taxation $(\mathcal{P})$ equals true PTE $(\mathcal{P}^*)$ times an exponential error ε which has a normal distribution:

$$\mathcal{P} = \mathcal{P}^*(\alpha)e^{\varepsilon}, \quad \varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$$

This measurement error assumption could accommodate a few microfoundations. It could arise from the measurement process, e.g., the reported numbers have different aggregation across units within a plant or typos. Plants may also face optimization frictions—$\mathcal{P}^*$ represents a plant's optimal PTE, but due to managerial errors or other forces, the plant ultimately picks a PTE $\mathcal{P}$ which differs from the truth. The tax bunching literature explores explicit models of these and other microfoundations (Kleven and Waseem 2013; Anagol et al. 2024).

To derive the conditional empirical distribution of observed PTE, we use a similar ap-

proach as above:

$$\mathbb{P}(x < \mathcal{P} \mid \varepsilon) = \begin{cases} 0 & \text{if } \ln \mathcal{P} - \ln \mathcal{P}_{min} < \varepsilon \\ \frac{\left[\mathcal{P}_{min}^{\gamma} - (\mathcal{P}e^{-\varepsilon})^{\gamma}\right]}{\left[\mathcal{P}_{min}^{\gamma} - T\mathcal{P}_{max}^{\gamma}\right]} & \text{if } \ln \mathcal{P} - \ln \overline{\mathcal{P}} < \varepsilon \leq \ln \mathcal{P} - \ln \mathcal{P}_{min} \\ \frac{\left[\mathcal{P}_{min}^{\gamma} - T(\mathcal{P}_r)^{\gamma}\right]}{\left[\mathcal{P}_{min}^{\gamma} - T\mathcal{P}_{max}^{\gamma}\right]} & \text{if } \ln \mathcal{P} - \ln \mathcal{P}_r < \varepsilon \leq \ln \mathcal{P} - \ln \overline{\mathcal{P}} \\ \frac{\left[\mathcal{P}_{min}^{\gamma} - T(\mathcal{P}e^{-\varepsilon})^{\gamma}\right]}{\left[\mathcal{P}_{min}^{\gamma} - T\mathcal{P}_{max}^{\gamma}\right]} & \text{if } \varepsilon \leq \ln \mathcal{P} - \ln \mathcal{P}_r \end{cases} \tag{18}$$

where T equals the scaled ratio of pollution taxes for major and minor sources (see Appendix equation C–9).

The four cases in equation (18) have sensible interpretation. In the first case, entrepreneurs with sufficiently low optimal PTE or negative errors exit, so have no PTE mass. The second case describes the PTE distribution for unconstrained minor sources. The third case describes the PTE distribution for constrained minor sources, which bunch at the threshold $\mathcal{P} = \overline{\mathcal{P}}$. The fourth case describes the PTE distribution for major sources, which have sufficiently high optimal PTE or positive error draw. The PTE of the smallest (minor) source, $\mathcal{P}_{min}$, appears in each case because it provides a parsimonious way to describe a combination of model parameters, derived by using the fact that a density integrates to one (appendix equation C–7).

Using a change of variables, the law of total probability, and properties of the normal distribution, we derive the unconditional distribution of PTE. Differentiating with respect to PTE and again using properties of the normal distribution yields the unconditional density of PTE:

$$\begin{aligned} \chi(\mathcal{P}) = C\mathcal{P}^{\gamma-1}e^{\frac{1}{2}\sigma_\varepsilon^2\gamma^2}\ \Phi(x)\Big|_{\frac{\ln(\mathcal{P})-\ln(\mathcal{P}_{min})}{\sigma_\varepsilon}+\sigma_\varepsilon\gamma}^{\frac{\ln(\mathcal{P})-\ln(\overline{\mathcal{P}})}{\sigma_\varepsilon}+\sigma_\varepsilon\gamma} \\ - \frac{1}{\sigma_\varepsilon \mathcal{P}} \frac{C}{\gamma} \left(\overline{\mathcal{P}}^{\gamma} - T\mathcal{P}_r^{\gamma}\right) \varphi\left(\frac{\ln(\mathcal{P}) - \ln(\overline{\mathcal{P}})}{\sigma_\varepsilon}\right) \\ + \frac{C}{\gamma} T\mathcal{P}^{\gamma-1}e^{\frac{1}{2}\sigma_\varepsilon^2\gamma^2}\gamma\Phi\left(\frac{\ln(\mathcal{P}) - \ln(\mathcal{P}_r)}{\sigma_\varepsilon} + \sigma_\varepsilon\gamma\right) \end{aligned} \tag{19}$$

where $\Phi(\cdot)$ and $\varphi(\cdot)$ represent the standard normal distribution and density.

Equation (19) describes the likelihood of observing the PTE distribution χ as a function of several terms. The likelihood depends on the major source threshold $\overline{\mathcal{P}}$ and the scaled ratio of major and minor source pollution taxes T. The likelihood also depends on several unknown terms—the emissions of the smallest source, $\mathcal{P}_{min}$; the constant γ; the emissions of the smallest major source $\mathcal{P}_r$; and the standard deviation of measurement error σ_ε. Section (6) estimates these unknown terms by choosing their values to maximize the likelihood

of observing the PTE density that our construction permits data actually report, i.e., Section 6 applies maximum likelihood to equation (19) to estimate the unknown parameters. Although the parameter γ itself does not have a simple interpretation, given estimates of the pollution elasticity β and the elasticity of substitution σ from existing literature, appendix equation (C–6) shows that estimating γ is isomorphic to estimating the dispersion of ability, β_α.

5.5 Recovering the Variable and Fixed Costs of Major Source Regulation

This subsection derives closed-form equations for the variable and fixed cost of major source regulations in terms of parameters and moments of the data. Substituting the first-order condition for abatement in (10) back into the emissions production function (4) gives an intuitive expression to estimate variable pollution taxes:

$$\tau = \frac{1}{\rho}\frac{\beta}{1-\beta}\frac{wn}{e} \tag{20}$$

This equation reflects the idea that with Cobb-Douglas production, factor payments are proportional to factor shares—$e\tau$ equals payments to pollution taxes, wn equals payments to labor, and β and $1-\beta$ are their factor shares. The term $1/\rho$ relates PTE to emissions. Section 5.5 uses estimates of each term on the right-hand side of equation (20) to infer the variable pollution tax, separately for major and minor sources. Allowing each term on the right-hand side of equation (20) to vary by plant will let us estimate industry- or plant-specific pollution taxes. While our previous work has analyzed changes in implicit pollution taxes over time using a related framework (Shapiro and Walker 2018), this may be the first estimate using this framework to estimate the level of implicit pollution taxes facing individual plants.

To estimate the fixed cost of major source regulation F, we use the indifference condition of the smallest major source:

$$\mathbb{E}\left[\pi|\mathcal{P}=\mathcal{P}_r,\alpha=\alpha_r\right] = \mathbb{E}\left[\pi|\mathcal{P}=\overline{\mathcal{P}},\alpha=\alpha_r\right] \tag{21}$$

The left-hand side of this equation (21) describes the expected profit of the smallest major source, which has productivity α_r, and so chooses to emit $\mathcal{P}=\mathcal{P}_r$. The right-hand side describes the expected profit of this firm if it instead chose to bunch at the threshold and emit $\mathcal{P}=\overline{\mathcal{P}}$. At an optimum, these two expected profit terms must be equal, otherwise the firm with $\alpha=\alpha_r$ would not be the smallest major source. Substituting in optimal choices of

unconstrained firms from equations (10) and (11), constrained firms from appendix equations (C–1) through (C–3), then solving for the fixed cost of major source regulation F, gives

$$
\begin{aligned}
F = \quad & \frac{\sigma^{-\sigma}\kappa_e^{\beta}}{\kappa_q}\Bigg[\left(\frac{1}{\sigma-1}\right)^{-\sigma}\left(\frac{\rho^{\beta}}{\alpha^{1-\beta}}\frac{\tau_1^{\beta}w^{1-\beta}}{\beta^{\beta}(1-\beta)^{1-\beta}}\right)^{1-\sigma}\left(\frac{1}{\sigma-1}+\beta\right) \\
& -\left(\frac{\alpha_r^{\beta-1}\bar{n}_r^{\beta}}{\bar{e}^{\beta}(\sigma-1)}\right)^{1-\sigma}\left[w+\frac{\tau_0\rho\bar{e}}{\bar{n}_r}\right]^{-\sigma}\left[w+\sigma\frac{\tau_0\rho\bar{e}}{\bar{n}_r}\right]\Bigg] \\
& -\tau_0\overline{\mathcal{P}}-\tau_1\mathcal{P}_r
\end{aligned}
\tag{22}
$$

Equation (22) provides a closed-form description of the fixed costs of major source regulation. Intuitively, it says that the fixed cost of major source regulation equals the value which makes the smallest major source, with PTE $\mathcal{P}_r$, indifferent between emitting $\mathcal{P}_r$ and suffering the costs of major source regulation, versus accepting the costs of decreasing its size, emitting $\overline{\mathcal{P}}$, and avoiding major source regulation. The two subtracted terms in brackets reflect this comparison, as they subtract versions of the pollution taxes that bunching minor sources pay from those that the smallest major sources pay. As discussed in Section 5.6, ongoing work for this paper estimates each term on the right-hand side of equation (22), then substitutes them into equation (22) to obtain an estimate in dollars of the fixed cost of major source regulation.

5.6 Counterfactuals

This subsection explains how we analyze counterfactual policies. Generally, we describe mean emissions and output in baseline data, and then under each potential counterfactual. The monetized ratio of these terms measures the social welfare impact of a counterfactual.

We focus on several types of counterfactual policies; each requires separate derivations of equations describing counterfactual emissions and output. The first counterfactual policy removes major source regulation, so that all firms become minor sources. The second counterfactual policy makes all firms major sources, and requires them to pay the fixed and variable costs of major source regulation. The third policy both makes all firms minor sources and increases the variable pollution tax so as to keep emissions constant. This provides the most direct measure of the costs of misallocation due to size-based regulation, holding emissions fixed. In other words, it answers the question: what if we obtained the same environmental outcome using pollution taxes rather than size-based regulation? The fourth modifies the fixed cost of major source regulation F to its optimal level, holding all other aspects of regulation fixed. The final counterfactual adjusts the major source threshold $\overline{\mathcal{P}}$ to its optimal level, holding other aspects of regulation fixed.

To analyze how a counterfactual policy affects emissions, we integrate the PTE density (16) across plants to describe the mean baseline PTE of existing sources:

$$\begin{aligned}\mathbb{E}[\mathcal{P}] = \quad & \frac{c_\alpha}{\kappa_q^{1-\sigma}}\rho\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\left(\frac{\beta}{\rho\tau_0\kappa_e}\right)^{1-\beta(1-\sigma)}\left(\frac{w}{1-\beta}\right)^{-\tilde{\beta}}\frac{\left[\overline{\alpha}^{\tilde{\beta}-\beta_\alpha+1}-\alpha_{min}^{\tilde{\beta}-\beta_\alpha+1}\right]}{\tilde{\beta}-\beta_\alpha+1} \\ & +\frac{c_\alpha\overline{\mathcal{P}}}{1-\beta_\alpha}\left[\alpha_r^{1-\beta_\alpha}-\overline{\alpha}^{1-\beta_\alpha}\right] \\ & +\frac{c_\alpha}{\kappa_q^{1-\sigma}}\rho\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\left(\frac{\beta}{\rho\tau_1\kappa_e}\right)^{1-\beta(1-\sigma)}\left(\frac{w}{1-\beta}\right)^{-\tilde{\beta}}\frac{\left[\alpha_{max}^{\tilde{\beta}-\beta_\alpha+1}-\alpha_r^{\tilde{\beta}-\beta_\alpha+1}\right]}{\tilde{\beta}-\beta_\alpha+1}\end{aligned} \tag{23}$$

where $\tilde{\beta} \equiv (\beta-1)(1-\sigma)$. Equation (23) provides an analytical description of mean PTE in terms of many model-based terms that we estimate and one we do not—α_{max}, the maximum possible productivity of an operating plant. Because the mean PTE in our construction data represents $\mathbb{E}[\mathcal{P}]$, we then use equation (23) to estimate α_{max}.

Integrating over the distribution of output and again using the PTE density from (16) gives the mean baseline output of operating firms:

$$\begin{aligned}\mathbb{E}[q] = \quad & \frac{c_\alpha}{\kappa_q^{-\sigma}}\left[\left(\frac{\sigma}{\sigma-1}\left(\frac{w}{1-\beta}\right)^{1-\beta}\left(\frac{\tau_0\rho\kappa_e}{\beta}\right)^{\beta}\right)^{-\sigma}\frac{\left[\overline{\alpha}^{\sigma(1-\beta)-\beta_\alpha+1}-\alpha_{min}^{\sigma(1-\beta)-\beta_\alpha+1}\right]}{[\sigma(1-\beta)-\beta_\alpha+1]}\right. \\ & +\left(\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}\int_{\overline{\alpha}}^{\alpha_r}\left(\frac{1}{1-a^c(\alpha)}\left(\frac{w}{\alpha}+\tau\rho\kappa_e(1-a^c(\alpha))^{\frac{1}{\beta}}\right)\right)^{-\sigma}\alpha^{-\beta_\alpha}d\alpha\right) \\ & \left.+\left(\frac{\sigma}{\sigma-1}\left(\frac{w}{1-\beta}\right)^{1-\beta}\left(\frac{\tau_1\rho\kappa_e}{\beta}\right)^{\beta}\right)^{-\sigma}\frac{\left[\alpha_{max}^{\sigma(1-\beta)-\beta_\alpha+1}-\alpha_r^{\sigma(1-\beta)-\beta_\alpha+1}\right]}{[\sigma(1-\beta)-\beta_\alpha+1]}\right]\end{aligned} \tag{24}$$

In the interest of parsimony and given that ongoing work is estimating these equations with data, we only describe theoretical results for one counterfactual here, though others involve somewhat similar results. We discuss the first counterfactual of making all firms minor sources. Equivalently, we we set $\tau_1' = \tau_0$ and $F' = 0$, where a prime ($'$) denotes the counterfactual value. We solve for the PTE of the smallest firm under this counterfactual, calculate the counterfactual PTE distribution, differentiate it to find the counterfactual PTE density, and then integrate to find mean counterfactual PTE and output under this counterfactual are as follows:

$$\mathbb{E}[q'] = \frac{c_\alpha}{\kappa_q^{-\sigma}} \left(\frac{\sigma}{\sigma - 1} \left(\frac{w}{1-\beta} \right)^{1-\beta} \left(\frac{\tau_0 \rho \kappa_e}{\beta} \right)^{\beta} \right)^{-\sigma} \frac{\left[\alpha_{max}^{\sigma(1-\beta)-\beta_\alpha+1} - \alpha_{min}^{\sigma(1-\beta)-\beta_\alpha+1} \right]}{[\sigma(1-\beta) - \beta_\alpha + 1]} \tag{25}$$

$$\mathbb{E}[\mathcal{P}'] = c_\alpha \rho \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} \left(\frac{w}{(1-\beta)} \right)^{(1-\beta)(1-\sigma)} \left(\frac{\beta}{\tau_0 \rho} \right)^{1-\beta(1-\sigma)} \frac{\left[\alpha_{max}^{(\beta-1)(1-\sigma)-\beta_\alpha+1} - \alpha_{min}^{(\beta-1)(1-\sigma)-\beta_\alpha+1} \right]}{(\beta-1)(1-\sigma) - \beta_\alpha + 1} \tag{26}$$

To assess how this counterfactual affects social welfare, we calculate the ratios of counterfactual to baseline mean PTE and output.

6 Model-Based Estimates

6.1 Model Diagnostics

This subsection uses four approaches to clarify how the model works and how much confidence we should give to its estimates. First, using the PTE microdata, we regress the log of a firm's rank in the PTE distribution on the log of its PTE. This tests the idea, following from assumption (2), that emissions follow a power-law distribution. Ongoing analysis is obtaining these results.

Second, we use Census microdata on each establishment i to estimate regressions corresponding to several key assumptions and intermediate results in the model:

$$lne_i = \alpha_0 + \alpha_1 ln(1 - a_i) + \alpha_2 lnn_i + \eta_i \tag{27}$$

$$lne_i = \beta_0 + \beta_1 lnw_i + \beta_2 ln\tau_i + \nu_i \tag{28}$$

$$lnn_i = \gamma_0 + \gamma_1 lnw_i + \gamma_2 ln\tau_i + \upsilon_i \tag{29}$$

These reflect model equations (4), (12), and (13). They use plant-level data on emissions e from the National Emissions Inventory, abatement a from the Pollution Abatement Costs and Expenditures survey, and employment and wages (n, w) from the Census of Manufactures. As a proxy for the stringency of regulation τ, we use indicators for nonattainment designations. Estimates of equations (27) through (29) assess whether broad patterns in the Census microdata reflect model predictions—for example, whether more tightly regulated plants have lower emissions, and whether plants with greater employment have greater emissions.

Third, we use a simulation to clarify model identification. We choose values of model parameters to reflect existing literature. We use these parameters in conjunction with the model to generate a simulated, artificial distribution of plants. For each simulated plant, the

model implies values of output, PTE, and prices. Finally, using the simulated population of plants, we apply model results to see if we can recover the parameter values originally used to generate the simulated firms. This simulation helps clarify the identification of model parameters. It can also show how different parameter values affect observed patterns in data. We have completed the generation of simulated plants from parameters, and ongoing work is using this simulation to clarify parameter identification.

Fourth, we directly assess model fit to the microdata. Figure 6 shows one example of such assessment. The blue circles in this figure show the share of firms with PTE in 30 bins of five PTE each. For example, the first circle shows the share of firms with PTE between 25 and 30; the second circle shows the share of firms with PTE between 30 and 35; etc. We restrict this sample to firms facing a major source threshold of 100, and the dashed vertical gray line at PTE=100 shows this cutoff. The solid red line shows the model's predictions of PTE throughout this distribution, using a preliminary calibration based on applying maximum likelihood to equation (19). The model accurately captures several broad features of the PTE distribution, including the overall power-law shape, the bunching below the threshold, and the lower density above the threshold. The model somewhat under-predicts firm density just below the threshold, and somewhat over-predicts it just above the threshold, perhaps in part because it assumes symmetric measurement error. We emphasize that the model is not showing a nonparametric fit to the microdata, but is instead predicting PTE based on the economic parameters and assumptions that the previous section describes.

6.2 Variable and Fixed Costs of Pollution Regulation

This subsection uses model results to to estimate the costs of pollution regulation, in several steps. We first use equation (20) to estimate implicit pollution taxes, i.e., the shadow price of pollution. Ongoing work is estimating these values using administrative microdata in the Census Research Data Center. We can obtain a preliminary estimate using mean values from public summaries of the Census of Manufactures. We estimate the ratio of emissions to PTE, from the inverse of Figure 3, as $\rho = 5$. We use the estimate of the pollution elasticity $\beta = 0.056$ for the dirtiest manufacturing industries, from Shapiro and Walker (2018). The mean US annual manufacturing wage in the year 2012 Census of Manufactures was $w = 52,915$, and the mean plant employed $n = 38$ workers. Finally, the 2012 National Emissions Inventory reports that the mean manufacturing plant reported $e = (8, 65, 13)$ short tons of particulate matter, nitrogen oxides, and volatile organic compounds, respectively.

Substituting these values into equation (20) implies that the implicit pollution tax per short ton for the mean manufacturing plant is \$2,961 for particulate matter, \$364 for nitro-

gen oxides, and $1,822 for volatile organic compounds. Of course, most US environmental regulation takes the form of standards, cap-and-trade markets, and other policies rather than pollution taxes, so these could be interpreted as the pollution tax which would be equivalent to the range of environmental regulations that the average plant faces. Clean Air Act offset markets provide one benchmark to use for these estimates. Air pollution offset markets, which trade offsets for entry of major sources, had mean prices in the 2010s of $1,126 per short ton for nitrogen oxides and $854 for volatile organic compounds. This value for nitrogen oxides is higher than the pollution tax we estimate, the value for volatile organic compounds is somewhat lower, though both are a broadly similar order of magnitude.

Ongoing estimates in the Census Research Data Center are obtaining estimates of these values for a common set of plants, using comparable methodology across plants. We are also estimating a distribution of implicit pollution taxes across plants, varying by plant-specific wages, employment, emissions, and other variables. Ongoing work is exploring how these plant-specific implicit pollution taxes vary with observable plant characteristics (e.g., nonattainment designations and industry).

Ongoing work in the Census Research Data Center also estimates the fixed cost of major source regulation, by constructing an empirical analogue to equation (22).

6.3 Analysis of Counterfactual Policies

This subsection discusses our approach to estimate how changing size-based regulation in the US Clean Air Act affects pollution emissions, output, and social welfare. We follow the methodology and counterfactuals from Section 5.6. Specifically, we calculate mean PTE in baseline data, and use equation (24) to estimate the mean quantity of output in baseline data. We use equations (26) and 25 to estimate mean PTE and output under a counterfactual scenario. We value the output at baseline prices observed from the Census of Manufactures, and we value the change in emissions using the AP3 integrated assessment model (sensitivity analyses are using EASIUR and InMAP). Ongoing work is outputting these results from the Census RDC.

7 Conclusions

Many of the world's largest environmental policies in the US, China, the EU, and elsewhere apply stricter regulation to firms with larger capacity, pollution, or output. Such size-based environmental regulation can target a large share of pollution, but may also generate aggregate costs by misallocating productive resources away from large and productive firms.

Environmental economics research has provided enormous insight into the properties of different environmental policy instruments, including cap-and-trade markets, pollution taxes, hybrid instruments, and standards. Research has devoted little effort, however, to assessing the effectiveness, efficiency, and cost effectiveness of size-based environmental regulation.

We describe a framework for studying the environmental and economic consequences of size-based environmental regulation and counterfactual policies. The framework combines canonical assumptions in the macro-labor, macro-trade, and environmental economics literatures. Our model provides closed-form equations that describe the fixed and variable costs of size-based regulation in terms of parameters and moments that microdata can measure. This framework can also naturally assess the effects of counterfactual policies, such as eliminating size-based regulation, choosing constrained optimal fixed costs or regulatory thresholds for large sources.

We apply these ideas to study US air pollution regulation. Under the US Clean Air Act, establishments with potential to emit (PTE) pollution above a given threshold, often 100 short tons per year, are declared to be "major sources." Major sources face tighter emission standards, greater fines, more frequent inspections, and generally greater regulatory scrutiny.

We collect, digitize, and harmonize establishment-level PTE data from construction permits in the eight states that could provide these data. We link these establishment records with plant-level data on enforcement actions, actual emissions, inputs, and outputs, using administrative data from the EPA and Census Bureau.

These microdata reveal substantial excess mass of firms slightly below major source thresholds. Firms facing a threshold of 25 tons per year are more likely to have PTE just below 25 tons and less likely to have PTE modestly above 25 tons. We observe similar bunching around 100 tons for firms facing a major source threshold of 100 tons. This bunching provides revealed preference evidence that major source regulation creates substantial costs for firms. The costs have a sufficient magnitude to cause firms to decrease capacity, install additional abatement technology, or adopt binding production limits to avoid major source regulation. A regulatory scrutiny index summarizing inspections, violations, and fines increases by half a standard deviation at the major source threshold, providing further evidence that major source regulation creates real costs to firms. Actual emissions readings from state inventories suggest that the PTE values used to determine which firms are major sources reflect unbiased estimates of emissions, rather than accounting manipulations.

This manuscript provides a preliminary and incomplete application of the model to estimate the shadow price of pollution emissions for the average US manufacturing plant. We estimate costs of several hundred to several thousand dollars per year, reflecting the combination of emissions standards, market-based instruments, and other regulations that plants

face. Ongoing work using administrative microdata in the Census Research Data Center is more flexibly estimating the fixed and variable costs of major source regulation. In addition, this work is estimating the environmental, economic, and social welfare impacts of counterfactual policies.

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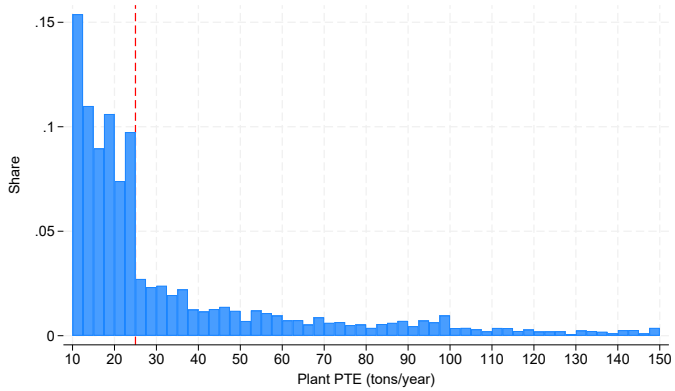
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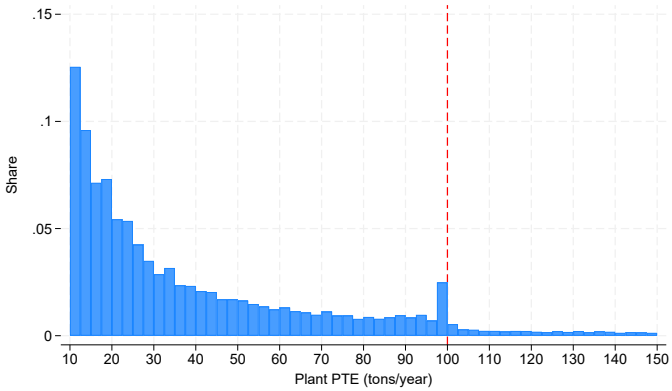
8 Figures and Tables

Figure 1: Bunching in Firm Density

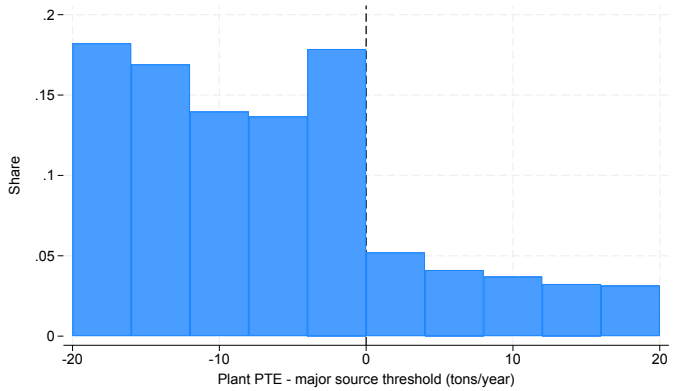
(a) Plants facing a threshold of 25 tons



(b) Plants facing a threshold of 100 tons

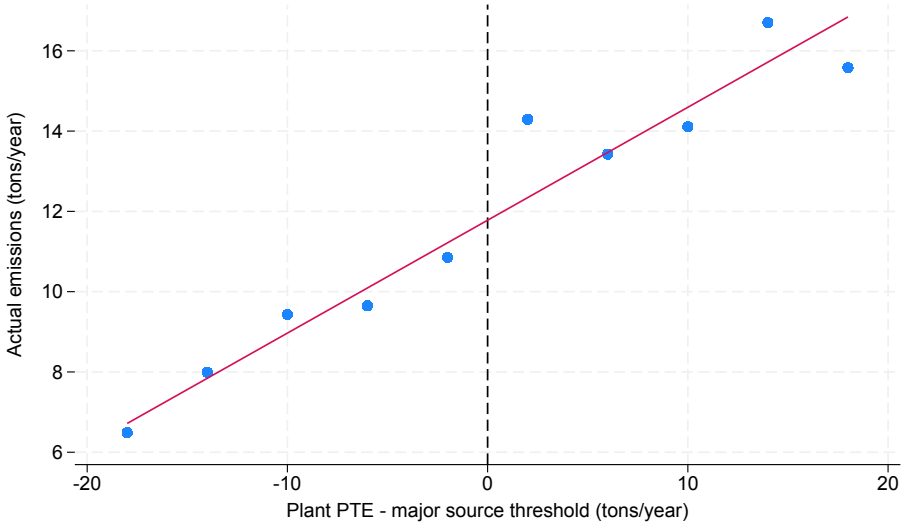


(c) Pooling thresholds



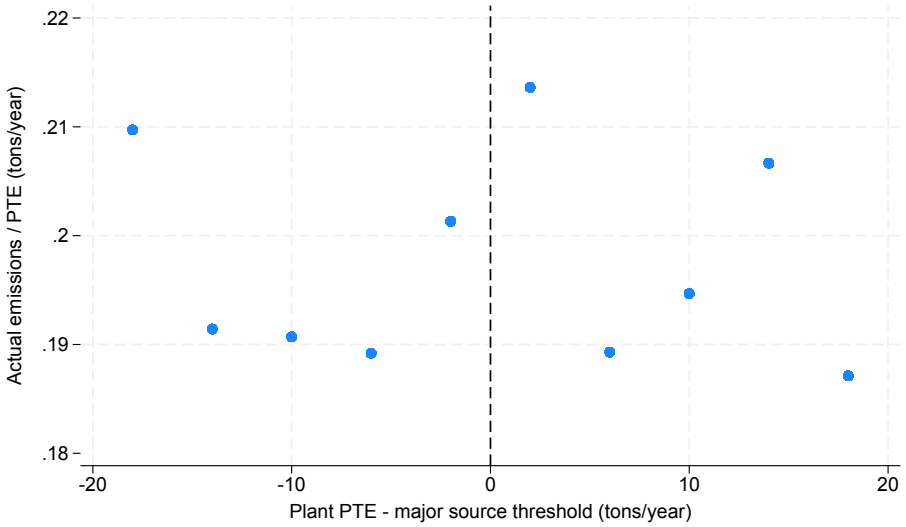
Notes: Each permit describes a plant×pollutant×year. Graphs give each plant equal weight. Panel (c) pools observations from panels (a) and (b). Data exclude Illinois plants which face thresholds at both 25 and 100 tons.

Figure 2: Actual Pollution Emissions Versus PTE



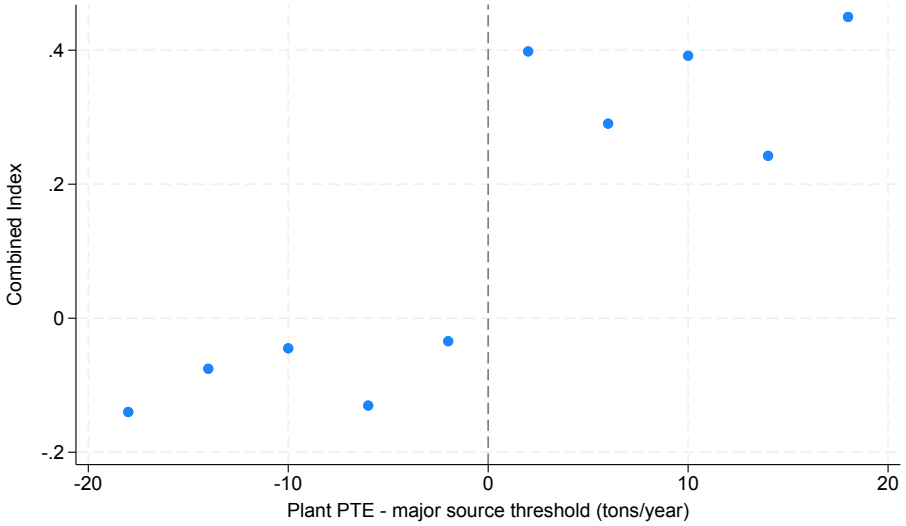
Notes: Blue circles show binned scatter plot, red line shows linear trend. Vertical axis is from state emissions inventories, horizontal axis is from construction permits.

Figure 3: Ratio of Pollution Emissions to PTE



Notes: Blue circles show binned scatter plot. Vertical axis is ratio of actual emissions from state emissions inventories to PTE from construction permits.

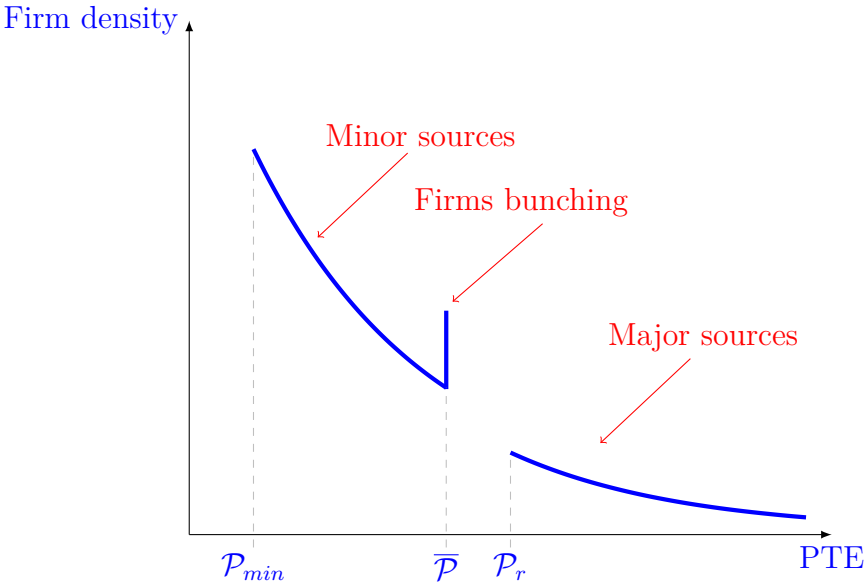
Figure 4: Enforcement Around Major Source Thresholds



Notes: Blue circles show binned scatter plot. Vertical axis is an index of regulatory enforcement actions, observed at the plant level from EPA Enforcement and Compliance History Online (ECHO) database. The index combines eight types of actions: compliance evaluations, certifications, formal actions, informal actions, formal actions with penalty, log penalty amount, high priority violations, and low priority violations.

Figure 5: Stylized Depiction of Model Cases

(a) Without measurement error



(b) With measurement error

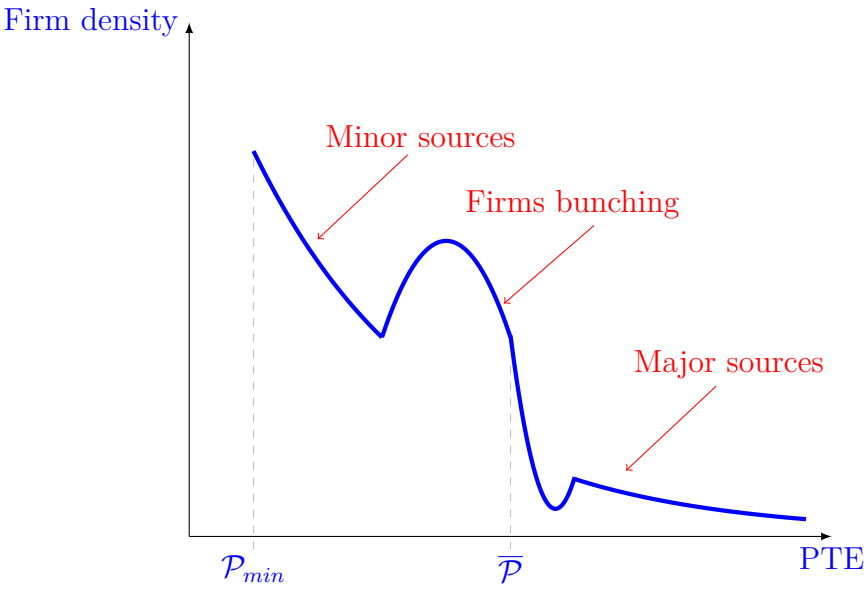
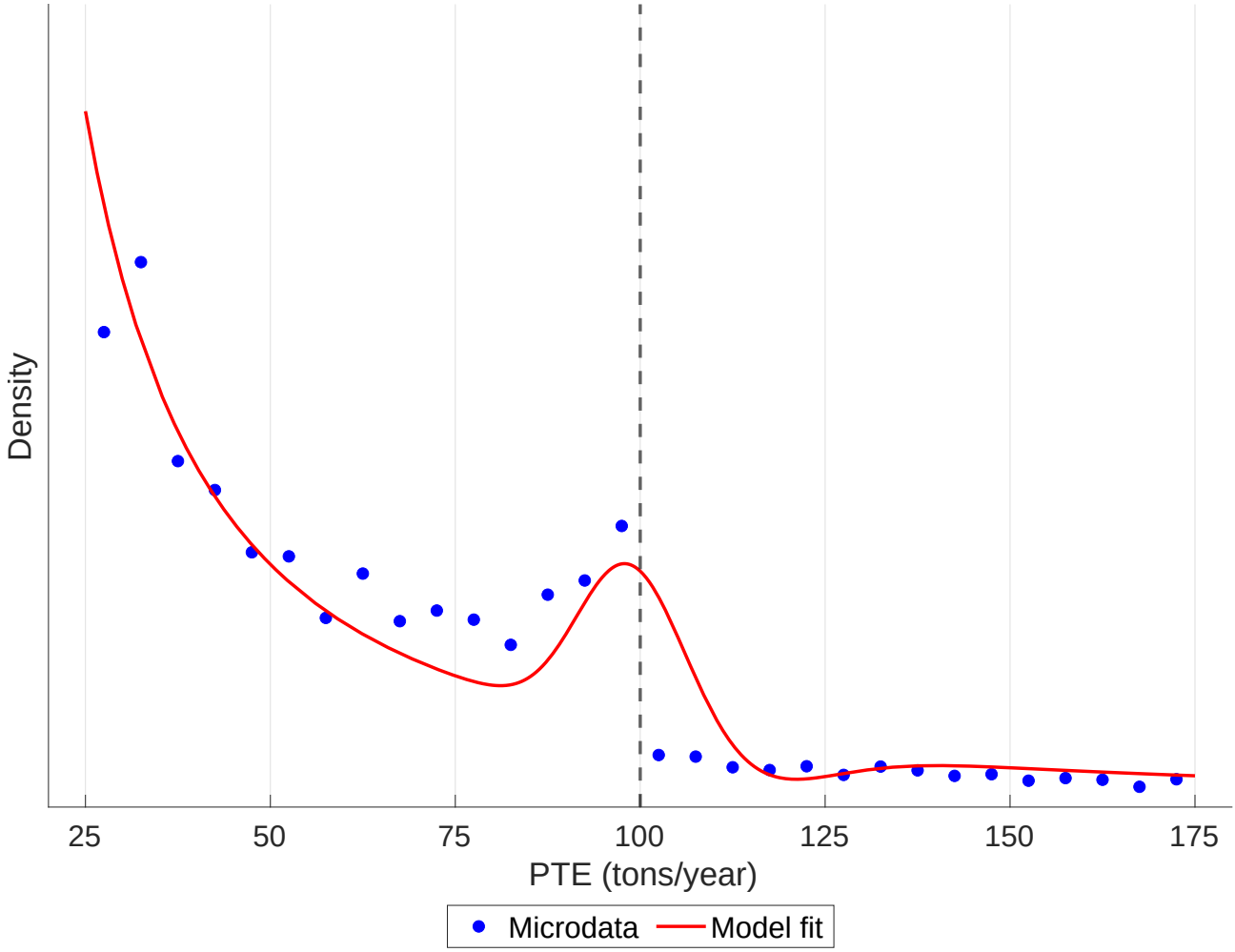


Figure 6: Model Fit



Notes: blue circles show binned means for firms facing a major source threshold of 100 tons PTE. Red line shows fit from model estimates.

Table 1: Prominent Examples of Size-Based Environmental Regulation

Region	Policy	Running variable	Cutoff	Regulations	Source
Canada	Canada Wide Standards	Emissions (t)	10	Standards	Najjar and Cherniwchan (2021)
China	CEMS	Emissions (t)		Monitoring	Buntaine et al. (2024)
EU	Industrial Emissions Directive	Thermal output		Many	European Union (2024)
EU	Emission Trading System	Emissions (tCO_2)	25,000	Allowances	Kurz (2024)
EU	Seveso Directives I-II-III	Quantity (t, etc.)	Many	Disaster prevention	Laurent et al. (2021)
S. Africa	Air Quality Act	Capacity		Standards	Naiker et al. (2012)
US	Clean Air Act	Potential to emit (t)	100	Many	This paper
US	Clean Water Act	CAFO size (t)	2,500	Many	Sneeringer and Key (2011)
US	Inflation Reduction Act	Methane emissions (t)	25,000	Fees	USEPA (2024*b*)
US	Safe Drinking Water Act	Customers	10,000	Many	USEPA (2024*a*)
US-CA	AB32	Emissions (tCO_2)	10,000	Fees	CARB (2024)

Notes: t represents tons, CAFO represents concentrated animal feeding operations, CEMS represents continuous emissions monitoring systems, AB32 is Assembly Bill 32 (California's cap-and-trade market for carbon), and CA is California. The running variable describes the variable that the regulation uses to measure size. Cutoff represents the value of the running variable at which regulation discretely becomes more stringent. Regulations describes the type of regulation the policy imposes.

Table 2: Description of PTE Microdata

	(1)
N (facility×pollutant×year)	417,352
N (facility)	36,825
Share by pollutant	
Carbon monoxide	0.10
Nitrogen oxides	0.22
Particulate matter	0.25
Sulfur dioxide	0.03
Volatile organic compounds	0.39
Share by state	
Illinois	0.50
Kentucky	0.14
Louisiana	0.19
Minnesota	0.03
Nevada	0.09
New Mexico	0.06
North Carolina	0.05
Washington	0.03
Share by decade	
1990s	0.17
2000s	0.27
2010s	0.44
2020s	0.11
Share by PTE threshold	
25	0.15
100	0.84

Notes: Each permit describes a plant×pollutant×year.

Online Appendix

Size-Based Environmental Regulation:
Evidence from Major Clean Air Act Thresholds

Bora Ozaltun Joseph S. Shapiro Reed Walker

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A Data: Details

This appendix is ongoing and will appear in future versions of the manuscript.

B Model Notation

Functions:

$f(n)$: production technology
$\pi(\alpha)$: firm profits
$G(n)$: potential output (with no abatement)
$\tilde{n}(\alpha)$: firm size as function of ability

Parameters and exogenous variables:

θ: output elasticity of labor
$w,\ w^*$: wage, general equilibrium wage
N: size threshold for being Major
β: output share of pollution in cobb-douglas
ρ: Correlation of PTE and emissions
η: Random error in PTE-emissions relationship
γ: Parameter combo $\gamma \equiv \dfrac{1-\beta_\alpha}{(\beta-1)(1-\sigma)}$, use to simplify CDF/PDF algebra
c_α, β_α: Constants in ability density: $\phi(\alpha) = c_\alpha \alpha^{-\beta_\alpha}$
C: Constant combination of parameters

Distributions (PDFs, CDFs, probabilities):

$\phi(\alpha)$: PDF of managerial ability
$\chi(n)$: PDF of firm size
$X(n)$: CDF of firm size
p: Share of workers who form a firm $= \mathbb{P}(\alpha \geq \alpha_{min})$
$\varphi(\cdot)$: standard normal PDF
$\Phi(\cdot)$: standard normal CDF

Policies:

F: fixed cost of being Major
τ, τ_0, τ_1: variable cost of PTE, below and above threshold
$T \equiv \left(\dfrac{\tau_1}{\tau_0}\right)^{1-\beta(1-\sigma)}$

Firm-specific variables:

$\alpha, \overline{\alpha}$: Productivityof arbitrary, bunching firms
$n, \overline{n}$: workers at arbitrary, bunching firms
y: firm output
e: emissions
a: share of potential output used for abatement
$\mathcal{P}, \overline{\mathcal{P}}$: PTE; PTE at major source threshold
$q, \overline{q}$: Units of production (quantity output) for arbitrary, bunching firms
ε: Normally distributed noise in reporting employment

Cutoffs

$\underline{\alpha}$: Minimum possible α
α_{min}, n_{min}: Minimum α to form a firm rather than be a worker; min firm size
α_c: Minimum value to bunch at threshold
α_r: Minimum value to be a large firm with $n \geq N$
α_{max}: Maximum possible α

C Additional Model Details

This appendix describes additional details for model results. The main text equations (11), (12), and (13) describe optimal price, employment, and emissions for a firm that does not choose to bunch at the threshold, i.e., with $\mathcal{P} \neq \overline{\mathcal{P}}$, or the knife-edge firm that would choose $\mathcal{P} = \overline{\mathcal{P}}$ even in the absence of major source regulation. Firms that bunch at the threshold do not follow these equations, since they would optimally emit more than $\overline{\mathcal{P}}$ in the absence of major source regulation, but constrain their choices of price, employment, and emissions to ensure $\mathcal{P} = \overline{\mathcal{P}}$.

The following equations describe optimal choices of firms that bunch at the major source threshold ($\mathcal{P} = \overline{\mathcal{P}}$) so are constrained:

$$\bar{q} = \frac{\kappa_q \bar{e}}{\kappa_e} \left[\frac{\alpha}{w} \frac{(\sigma - 1)}{\sigma} \left(\frac{\kappa_q \bar{e}}{\kappa_e} \right)^{-1/\sigma} (1 - \beta) \kappa_q \right]^{\frac{\sigma(\beta-1)}{\beta - \beta\sigma - 1}} \tag{C–1}$$

$$\bar{p} = \left(\frac{\kappa_q \bar{e}}{\kappa_e} \left[\frac{\alpha}{w} \frac{(\sigma - 1)}{\sigma} \left(\frac{\kappa_q \bar{e}}{\kappa_e} \right)^{-1/\sigma} (1 - \beta) \kappa_q \right]^{\frac{\sigma(\beta-1)}{\beta - \beta\sigma - 1}} \right)^{-1/\sigma} \tag{C–2}$$

$$\bar{n} = \frac{\bar{e}}{\alpha \kappa_e} \left[\frac{\alpha}{w} \frac{(\sigma - 1)}{\sigma} \left(\frac{\kappa_q \bar{e}}{\kappa_e} \right)^{-1/\sigma} (1 - \beta) \kappa_q \right]^{-\frac{\sigma}{\beta - \beta\sigma - 1}} \tag{C–3}$$

We first discuss derivation of the conditional density of PTE. We separately derive the density of PTE for four groups of firms: the smallest firm; minor sources; firms that bunch at the cutoff; and major sources.

We first consider the smallest firm, with PTE and ability $(\mathcal{P}_{min}, \alpha_{min})$. To simplify PTE for this case from equation (14) in the main text, we utilize a free entry condition, which states that this firm must have expected profits equal to the wage:

$$w = \mathbb{E}[\pi \mid \mathcal{P} = \mathcal{P}_{min}]$$

Substituting in the equations for profit (6) and optimal firm decisions (10), (11), (13), and (14) yields

$$\mathcal{P}_{min} = \frac{w(\sigma - 1)\beta}{\tau_0} \tag{C–4}$$

The simple form of Equation (C–4) reflects a few ideas: variable profits in Melitz models equal r/σ for revenues r; production is Cobb-Douglas in pollution, from equation (5), so β is the cost share of pollution, with total pollution tax payments for the smallest source equal to $\mathcal{P}_{min}\tau_0$; w is the smallest firm's expected profit; and $\sigma/(\sigma - 1)$ is the markup.

Second, we describe the density of PTE for minor sources. Using the density definitionand again substituting in the plant's optimal decisions, we obtain the density for minor sources

$$\chi^*(\mathcal{P}|\mathcal{P}_{min} \leq \mathcal{P} < \overline{\mathcal{P}}) = C\mathcal{P}^{\gamma-1} \tag{C–5}$$

using the parameter combination

$$\gamma \equiv \frac{1 - \beta_\alpha}{(\beta - 1)(1 - \sigma)} \tag{C–6}$$

and constant

$$C \equiv \frac{c_\alpha}{(\beta - 1)(1 - \sigma)} \frac{1}{z} \left[\rho \left(\frac{\sigma}{\sigma - 1} \right)^{-\sigma} \left(\frac{\beta}{\rho\tau_0} \right)^{1-\beta(1-\sigma)} \left(\frac{w}{(1 - \beta)} \right)^{(1-\beta)(1-\sigma)} \right]^{-\gamma} \tag{C–7}$$

Third, we describe the PTE density for sources that bunch at the major source threshold. Except for the atomistic firm with $\alpha^* = \overline{\mathcal{P}}$, these firms are constrained—without major source regulation they would choose $\mathcal{P}^* \in (\overline{\mathcal{P}}, \mathcal{P}_r)$, where $\mathcal{P}_r$ represents the PTE of the smallest major source. Due to major source regulation, however, no plants choose PTE in $\mathcal{P}^* \in (\overline{\mathcal{P}}, \mathcal{P}_r)$, and all plants with $\alpha \in [\overline{\alpha}, \alpha_r]$ choose $\mathcal{P} = \overline{\mathcal{P}}$. A change of variables and the

plant's constrained optimal decisions give

$$\chi^*(\overline{\mathcal{P}}) = -\frac{C}{\gamma}\left[(\overline{\mathcal{P}})^\gamma - T(\mathcal{P}_r)^\gamma\right] \tag{C–8}$$

Here we define the scaled ratio of pollution taxes for major versus minor sources as

$$T \equiv \left(\frac{\tau_1}{\tau_0}\right)^{\gamma(1-\beta(1-\sigma))} \tag{C–9}$$

Finally, for unconstrained major sources, we use the plant's optimal decisions to obtain

$$\chi^*(\mathcal{P}|\mathcal{P} \geq \mathcal{P}_r) = CTP^{\gamma-1} \tag{C–10}$$

We use the fact that a density integrates to one, along with the previous conditional densities, to obtain a simpler expression for the constant C:

$$C = -\gamma P_{min}^{-\gamma} \tag{C–11}$$

C.1 Empirical Conditional Distributions

This subsection describes derivations of the empirical distributions of PTE, conditional on the error draws ε, for the four groups of firms.

First, entrepreneurs with $\mathcal{P}^* < \mathcal{P}_{min}$ choose not to enter. Equivalently, we describe this group as

$$\ln \mathcal{P} - \ln \mathcal{P}_{min} < \varepsilon$$

Second, entrepreneurs with $\mathcal{P}_{min} \leq \mathcal{P}^* < \overline{\mathcal{P}}$ become unconstrained minor sources. We can equivalently describe these firms as

$$\ln \mathcal{P} - \ln \overline{\mathcal{P}} < \varepsilon \leq \ln \mathcal{P} - \ln \mathcal{P}_{min}$$

Integrating over the conditional density from (17) and substituting in the plant's optimal PTE, these firms have the distribution of PTE, conditional on the error, as

$$\mathbb{P}(x < \mathcal{P} \mid \varepsilon) = 1 - \mathcal{P}_{min}^{-\gamma}(\mathcal{P}e^{-\varepsilon})^\gamma \tag{C–12}$$

Third, entrepreneurs with $\overline{\mathcal{P}} \leq \mathcal{P}^* < \mathcal{P}_r$ bunch at the major source threshold. We equivalently describe these firms as

$$\ln \mathcal{P} - \ln \mathcal{P}_r < \varepsilon \leq \ln \mathcal{P} - \ln \overline{\mathcal{P}}$$

Again integrating over the conditional density from (17) and using the conditional empirical distribution for unconstrained minor sources, we obtain the empirical distribution, conditional on the error, as

$$\mathbb{P}(x < \mathcal{P} \mid \varepsilon) = 1 - \mathcal{P}_{min}^{-\gamma} T \mathcal{P}_r^{\gamma} \tag{C–13}$$

Fourth, major sources are unconstrained with $\mathcal{P}^* \geq \mathcal{P}_r$. Equivalently, we can describe these firms as

$$\ln \mathcal{P} - \ln \mathcal{P}_r \geq \varepsilon$$

Integrating over the conditional density from (17) and using the empirical conditional distribution of bunching firmsgives

$$\mathbb{P}(x < \mathcal{P} \mid \varepsilon) = 1 - \mathcal{P}_{min}^{-\gamma} T (\mathcal{P} e^{-\varepsilon})^{\gamma} \tag{C–14}$$

D Appendix Figures and Tables

Figure A1: Example Permit

Entergy-Arkansas, Inc. Lynch Plant
Permit No.: 019-AOP-R2
CSN: 60-0087

Emissions from the facility include sulfur dioxide, nitrogen oxides, and particulates. A summary of facility wide emissions is provided in the following table. Specific emission unit information is located by the indicated cross reference pages.

EMISSION SUMMARY					
Source No.	**Description**	**Pollutant**	**Emission Rates***		**Cross Reference Page**
			lb/hr	**tpy**	
Total Allowable Emissions		PM_{10}	23.1	5.2	
		PM	58.5	24.1	
		SO_2	1305.5	285.9	
		VOC	16.6	13.0	
		CO	626.4	137.2	
		NO_x	1713.1	375.2	

Figure A2: Enforcement Around Major Source Thresholds, by Action Type

