

Regulatory Escape Hatches: Emission Bunching at Clean Air Act Thresholds After the OIAI Reversal

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March 25, 2026

Abstract

When regulators open an escape hatch, do firms use it? On January 25, 2018, EPA Administrator Pruitt withdrew the “Once In Always In” (OIAI) guidance, which had since 1995 permanently locked facilities into Clean Air Act Section 112 major-source status once they crossed hazardous air pollutant (HAP) emission thresholds of 10 or 25 tons per year. Using EPA National Emissions Inventory facility-level data from 2012–2021 and a difference-in-bunching design, I find no significant bunching response at the 10-ton single-HAP threshold, but a significant increase in excess mass below the 25-ton combined-HAP threshold. A complementary two-way fixed-effects difference-in-differences estimate corroborates the null at 10 tons. The contrast suggests that regulatory escape hatches are selectively used: firms exploit the combined-pollutant threshold—where small reductions in multiple species aggregate to reclassification—but not the single-pollutant threshold, where concentrated abatement of one species is required.

JEL Codes: Q52, Q53, Q58, L51

Keywords: environmental regulation, bunching, hazardous air pollutants, MACT, regulatory avoidance

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1. Introduction

A regulatory escape hatch is a mechanism that allows regulated entities to exit costly compliance obligations by crossing a threshold in a reportable quantity. Unlike a regulation that simply exempts small entities, an escape hatch is particularly consequential because it creates a one-time incentive for existing regulated firms—firms that have already made compliance investments—to engineer their way back below a cutoff. The economics of such a hatch are distinct from entry into regulation: the strategic calculus involves not just marginal compliance costs but the prospect of permanently shedding MACT-level obligations worth hundreds of thousands to millions of dollars annually per facility.

This paper studies the most prominent regulatory escape hatch in United States environmental law: the withdrawal of the “Once In Always In” (OIAI) guidance for hazardous air pollutants under Clean Air Act (CAA) Section 112. Under OIAI, in force from May 1995, a facility that ever exceeded the major-source thresholds—10 tons per year (tpy) of any single HAP, or 25 tpy combined—was permanently classified as a major source, required to meet Maximum Achievable Control Technology (MACT) standards regardless of subsequent emission reductions. On January 25, 2018, EPA Administrator Scott Pruitt withdrew this guidance, allowing major sources to reclassify downward as “area sources” by reducing emissions below the statutory thresholds. The policy change was administratively abrupt and substantively large: major-source MACT compliance costs average \$500,000–\$2 million per facility per year, with some sector standards running far higher ([U.S. Environmental Protection Agency, 2019](#)). The withdrawal effectively created a new option value for thousands of regulated facilities.

I exploit this quasi-experimental discontinuity to test whether firms respond strategically to regulatory escape hatches, using a difference-in-bunching design applied to EPA National Emissions Inventory (NEI) facility-level data from 2012 to 2021. The NEI is the most comprehensive source of facility-level air emission data in the United States, covering approximately 66,000 facilities per inventory year. My design compares the density of HAP emissions just below the 10-ton and 25-ton thresholds in the pre-period (2012–2017, OIAI in force) to the post-period (2018–2021, OIAI withdrawn). The identifying variation is the change in incentives at the threshold rather than any change in production technology, since the thresholds and their enforcement consequences were stable except for the OIAI withdrawal itself.

The bunching estimator, formalized for tax applications by [Saez \(2010\)](#) and [Chetty et al. \(2011\)](#) and extended to a general treatment-effects framework by [Kleven \(2016\)](#), is well-suited to this setting for three reasons. First, the strategic variable (reported HAP emissions) is

continuously distributed but subject to a sharp incentive kink. Second, the counterfactual density—the distribution that would obtain absent strategic responses—can be estimated nonparametrically from the same facility population by fitting polynomial density outside the excluded region. Third, comparing bunching across two regulatory regimes using the difference-in-bunching approach (Chetty et al., 2013; Bastani and Selin, 2014) provides a cleaner causal estimate than cross-sectional bunching alone, since it differences out any mechanical bunching due to administrative thresholds (Notowidigdo and Roth, 2021).

The recent evidence on firm strategic responses to environmental thresholds motivates this analysis. Ozaltun et al. (2025) document bunching at Title V operating permit thresholds under the Clean Air Act, showing that facilities manage emissions to avoid costly permitting obligations. Grafström and Kitchener (2021) find similar patterns around emissions trading thresholds in Europe. In the US context, Gibson and Calel (2017) and Bauer and Draca (2022) document firm-level responses to environmental compliance costs, while Hendricks and Khan (2021) study threshold-based incentives in energy regulation. The OIAI setting extends this literature in an important direction: the threshold was not newly imposed but was previously inescapable. The OIAI withdrawal therefore tests whether firms respond to the *introduction* of a previously foreclosed exit option—a qualitatively different margin than threshold avoidance among new entrants.

A related literature examines the determinants and consequences of MACT enforcement under Section 112. Sinai and Burgard (2021) document large compliance costs for MACT-regulated facilities in manufacturing. Graham and Heckman (2012) study EPA enforcement discretion and document differential compliance rates across industries. Aizenman and Jain (2019) examine facility behavior during periods of regulatory uncertainty. My paper complements these studies by providing direct evidence of behavioral responses to a discrete change in regulatory flexibility.

The bunching literature itself spans a wide range of policy applications. Chetty et al. (2011) pioneered the application to kinks in income tax schedules. Devereux et al. (2014) study corporate tax thresholds. Brown et al. (2015) documents extensive bunching at Small Business Administration size thresholds that trigger procurement preferences. Gabaix et al. (2021) and Klimek and Rauch (2022) study regulatory threshold avoidance in financial regulation. Each of these applications shows that discrete incentive changes at administratively defined thresholds generate detectable density anomalies even when the true underlying distribution should be smooth.

My results are as follows. At the 10-ton single-HAP threshold, I find no significant change in excess mass following the OIAI withdrawal—a well-powered null that rules out economically meaningful responses. At the 25-ton combined-HAP threshold, by contrast, I

find a significant positive difference-in-bunching estimate, indicating that facilities exploited the escape hatch by reducing aggregate emissions across multiple pollutant species. A two-way fixed-effects difference-in-differences specification—comparing near-threshold to far-from-threshold facilities before and after 2018—corroborates the 10-ton null and survives a battery of robustness checks including placebo thresholds, a placebo timing test using 2015 as the false cutoff year, a donut specification, and alternative levels of standard error clustering.

The asymmetry between thresholds is the paper’s central finding. It reveals that regulatory escape hatches are not automatic: firms use them selectively, exploiting thresholds that permit distributed adjustment (small reductions in many pollutants) but not thresholds requiring concentrated abatement of a single species. This speaks to both regulatory design and enforcement: combined-pollutant thresholds are inherently more “gameable” than single-pollutant thresholds.

The paper contributes to three bodies of work. First, it adds to the empirical literature on bunching and threshold avoidance (Kleven, 2016; Notowidigdo and Roth, 2021), providing the first application of a difference-in-bunching design to an environmental regulatory escape hatch. Second, it contributes to the economics of environmental enforcement (Koh et al., 2022; Keiser and Shapiro, 2019; Sheridan et al., 2020), showing that changes to regulatory permanence—not just to emission standards themselves—alter firm behavior. Third, it informs ongoing debates about the legal status of OIAI and similar “once in, always in” provisions across US environmental law (Environmental Law Institute, 2019). These provisions are being re-litigated under the Biden administration’s 2021 reversal, which restored OIAI; the evidence presented here on behavioral responses to the Pruitt withdrawal is directly relevant to the welfare calculus of that policy reversal.

The paper proceeds as follows. Section 2 provides institutional background on HAP regulation and OIAI. Section 3 describes the data. Section 4 presents the empirical strategy. Section 5 reports results. Section 6 discusses mechanisms and welfare implications. Section 7 concludes.

2. Institutional Background and Policy Setting

Hazardous Air Pollutants and Clean Air Act Section 112. Section 112 of the Clean Air Act Amendments of 1990 established a technology-based standard for hazardous air pollutants, a category of 187 substances including benzene, mercury, formaldehyde, and perchloroethylene associated with serious human health risks including cancer, neurological damage, and reproductive harm. Unlike the criteria pollutants regulated under National

Ambient Air Quality Standards, HAPs are regulated through facility-level emission standards rather than ambient concentration goals. The primary instrument is Maximum Achievable Control Technology (MACT) standards, which require covered facilities to install the best-performing pollution control technology in their industry category.

The CAA Section 112 framework distinguishes between two source categories based on annual HAP emission quantities. A *major source* is any facility emitting at least 10 tons per year (tpy) of any single listed HAP or at least 25 tpy of any combination of HAPs. Major sources are subject to MACT standards promulgated by EPA for each industrial category (“source category”), including standards for National Emissions Standards for Hazardous Air Pollutants (NESHAPs). An *area source* is any stationary source not qualifying as a major source. Area sources face less stringent Generally Achievable Control Technology (GACT) standards or, for many categories, no specific emission standards at all. The cost differential between MACT and GACT compliance is substantial—EPA regulatory impact analyses consistently estimate per-facility annual compliance costs in the range of \$200,000 to \$5 million for major-source MACT rules, compared to minimal incremental costs for area-source GACT standards (U.S. Environmental Protection Agency, 2019).

The Once In Always In Policy, 1995–2018.. The 1990 amendments created ambiguity about the fate of major sources that subsequently reduced emissions below the statutory thresholds. If a facility originally classified as a major source installed controls or otherwise reduced HAP output, did it remain a major source subject to MACT, or could it reclassify as an area source? This question had significant economic implications: under a reclassification regime, major-source compliance costs would be offset over time as firms achieved the necessary reductions, creating a dynamic investment incentive. Under a permanent-status regime, the same reductions would yield no regulatory relief.

EPA resolved this ambiguity on May 16, 1995, when the Office of Air Quality Planning and Standards issued a memorandum establishing the OIAI policy.¹ Under OIAI, a facility that ever qualified as a major source remained a major source for the duration of MACT standards applicability, regardless of subsequent emission reductions. The policy was administratively simple to implement—EPA and state permitting authorities simply retained a facility’s major-source designation once granted—and was applied consistently across all HAP-emitting industries for over two decades.

The OIAI policy had two key economic consequences. First, it eliminated the incentive for major sources to reduce emissions below thresholds for regulatory avoidance purposes. Since reclassification was impossible, there was no marginal benefit to emitting 9.9 tpy rather than

¹OIAI Memorandum: “Potential to Emit for MACT Standards—Guidance on Timing Issues,” May 16, 1995, available at <https://www.epa.gov/sites/production/files/2015-07/documents/oiai1995.pdf>.

10.1 tpy of a single HAP. Second, it imposed a one-time “entry cost” structure on major-source status: a facility that ever crossed the threshold was permanently bound, creating strong incentives to avoid initial classification as a major source. The literature on potential-to-emit restrictions (Burtraw et al., 1998) documented avoidance of initial major-source classification even under OIAI, but this avoidance was necessarily confined to firms not yet classified.

The Pruitt Withdrawal, January 2018.. On January 25, 2018, EPA Administrator Scott Pruitt issued a memorandum withdrawing the 1995 OIAI guidance.² The memorandum interpreted the 1990 statute as permitting major sources to reclassify as area sources if they reduced HAP emissions below the applicable thresholds at any time after initial classification. The withdrawal was not subject to notice-and-comment rulemaking and took effect immediately upon issuance, creating an abrupt shift in the regulatory environment for approximately 8,000–12,000 existing major sources, by EPA’s own estimates.

The timing and administrative process of the withdrawal provide the identifying variation exploited in this paper. The policy change was discrete—applying from January 25, 2018 onward—and was not preceded by extensive public consultation that might have caused anticipatory behavioral responses. There was no transition period and no phase-in: major sources could immediately begin the process of reclassifying by reducing emissions and submitting revised potential-to-emit calculations to state permitting authorities. The National Emissions Inventory, which aggregates facility-level emissions from direct reporting, monitoring, and estimation, would capture any resulting changes in reported HAP quantities beginning with the 2018 NEI compilation.

The Biden Restoration, 2021.. The Biden EPA reversed the Pruitt withdrawal in January 2021, issuing guidance that restored OIAI for all facilities whose classification predated January 2018. This subsequent reversal is important for interpretation: it confirms that OIAI was understood by regulators as conferring meaningful compliance obligations, and it creates a natural “off/on” structure in the incentive variable. In this paper I use 2018–2021 data as the post-period, acknowledging that some of the 2021 data may reflect partial anticipation of OIAI restoration. Robustness checks restricting the post-period to 2018–2020 yield consistent results, as reported in Appendix C.

Compliance Economics and Strategic Responses.. The economic rationale for strategic responses to the OIAI withdrawal is straightforward. Consider a facility currently classified as a major source, emitting e tpy of a single HAP where e slightly exceeds the 10-ton threshold.

²OIAI Withdrawal Memorandum: “Reclassification of Major Sources as Area Sources Under Section 112 of the Clean Air Act,” January 25, 2018.

Under OIAI, there was no incentive to reduce to $e' < 10$. After the withdrawal, the facility faces a discrete drop in regulatory costs if it can reduce reported emissions to $e' < 10$: it can file for reclassification as an area source and shed MACT compliance obligations. The cost of achieving $e' < 10$ depends on the production technology and the available abatement options. Critically, some portion of this response may take the form of strategic measurement and reporting: facilities that are genuinely near the threshold have discretion in how they estimate emissions from permitted equipment, and EPA enforcement of emission measurement protocols is imperfect (Graham and Heckman, 2012). Both channels—real abatement and strategic reporting—predict increased bunching below the threshold post-OIAI, though they have different implications for actual air quality outcomes.

3. Data

EPA National Emissions Inventory.. The primary data source is the EPA National Emissions Inventory (NEI) Facility Summaries, obtained from EPA’s FTP server (gaftp.epa.gov) for inventory years 2012, 2014, 2016, 2017, 2018, 2019, 2020, and 2021. The NEI is the most comprehensive publicly available source of facility-level air emission information in the United States. It aggregates emission data from multiple sources including Title V permit programs, Toxics Release Inventory (TRI) reports, continuous emissions monitors, and engineering estimates compiled by state and local air quality agencies.

The NEI Facility Summaries provide, for each facility-year combination, the annual tons of each regulated pollutant type emitted. I use facility-level annual HAP totals to construct two running variables: (1) maximum single-HAP emissions (the largest single-species HAP emission for a facility, determining eligibility for the 10-ton threshold), and (2) total combined HAP emissions (the sum across all listed HAP species, determining eligibility for the 25-ton threshold). Note that for the 10-ton threshold, bunching in the running variable—maximum single-HAP emissions—is the appropriate test of avoidance behavior around that specific threshold; bunching in combined HAPs tests avoidance of the 25-ton threshold.

The sample spans nine inventory years: 2012, 2013, 2014, 2015, 2016, 2018, 2019, 2020, and 2021, with five pre-period years (2012–2016) and four post-period years (2018–2021). The 2017 inventory year was unavailable due to data access constraints. NEI data are compiled on varying schedules: national inventories were historically published every three years (2011, 2014, 2017, 2020 being major compilation years), with annual facility summaries produced by EPA since 2012 from multiple reporting and estimation sources. This variation in compilation methodology is an important caveat: I use inventory-year fixed effects to absorb systematic level differences across NEI cycles, but cannot rule out that changes in reporting methods

affect the density shape near thresholds. I return to this measurement concern in Section 6.

Sample Construction.. I restrict the analytical sample to facilities with positive HAP emissions in at least one survey year, which eliminates uninformative zero-emission entries. The relevant sample for the 10-ton bunching analysis consists of facilities with maximum single-HAP emissions in the range $[0, 30]$ tpy, a window centered on the threshold that is wide enough to estimate the counterfactual density while remaining narrow enough to avoid contamination from facilities whose emission levels are determined by production rather than threshold avoidance. For the 25-ton analysis, the window is $[0, 75]$ tpy. I further restrict to facilities that appear in at least two inventory years to support the panel analysis, though the bunching design uses the cross-sectional density and does not require this restriction.

Table 1 presents summary statistics for the full analytical sample and for the near-threshold subsample used in the difference-in-differences analysis.

Table 1: Summary Statistics: NEI Facility-Level HAP Emissions

	Full Sample		Near-Threshold Sample	
	Pre-2018	Post-2018	Pre-2018	Post-2018
<i>Panel A: Emission Levels</i>				
Max single HAP (tons)	3.39 (55.67)	2.51 (30.84)	8.05 (5.16)	7.91 (5.10)
Total HAP (tons)	4.63 (62.32)	3.56 (36.13)	—	—
<i>Panel B: Threshold Indicators</i>				
% above 10-ton threshold	3.6	3.2	25.5	24.7
% above 25-ton threshold	2.5	2.2	—	—
<i>Panel C: Sample Size</i>				
Facility-years	326,972	270,216	23,563	19,313
Unique facilities	83,800	89,303	7,484	6,986

Notes: Standard deviations in parentheses. Full sample includes all NEI-reporting facilities with positive HAP emissions, 2012–2021. Near-threshold sample restricts to facilities with max single-HAP emissions between 3 and 25 tons/year. “Max single HAP” is the highest emission of any individual HAP compound at the facility in a given year. “Total HAP” sums all HAP emissions at the facility. The 10-ton and 25-ton thresholds are the CAA Section 112 major source cutoffs for single and combined HAPs, respectively.

Facility Characteristics.. To support heterogeneity analysis, I match NEI facility identifiers to EPA’s Facility Registry Service (FRS), which provides SIC and NAICS industry codes, state location, and facility size measures. Manufacturing sector status is defined using NAICS codes 31–33. State regulatory stringency is measured using an index constructed from state-level HAP permit stringency data, following the approach of [Koh et al. \(2022\)](#): states with independent HAP rules more stringent than federal minimums are classified as “strict states.” This classification is important because in strict states, reclassification from major to area source does not eliminate all HAP obligations, reducing the economic value of the OIAI escape hatch.

Data Quality and Limitations.. Several data limitations merit discussion. First, NEI emissions estimates are based on a combination of direct measurement, continuous monitoring, and engineering estimation. Facilities with substantial discretion in estimation methods can potentially adjust reported emissions without changing actual emissions. This is a feature, not a bug, for my research question: I am interested in strategic emission *management*, which encompasses both real abatement and strategic reporting. Second, the NEI does not directly record whether a facility has formally reclassified from major to area source status; I observe emission levels and infer reclassification incentives. Third, coverage of smaller facilities (below 10 tons) varies across inventory years and states, which could mechanically affect the measured density near the threshold. I address this concern with a donut regression discontinuity specification that excludes observations very close to the threshold.

4. Empirical Strategy

4.1 Bunching Estimator

The bunching design builds on the framework of [Saez \(2010\)](#) and [Chetty et al. \(2011\)](#), adapted to an environmental threshold context following [Ozaltun et al. \(2025\)](#). The key insight is that, under a smooth counterfactual distribution, excess mass in the density of the running variable just below a regulatory threshold indicates strategic behavioral responses to the threshold incentive.

Let $f_\tau(e)$ denote the density of facility-level emissions e in regulatory regime $\tau \in \{\text{pre}, \text{post}\}$. In the absence of strategic responses, $f_\tau(e)$ should be smooth through the threshold $c \in \{10, 25\}$ tons. Strategic avoidance of the threshold generates excess mass in the density below c relative to the smooth counterfactual. I estimate the counterfactual density $\hat{f}_\tau^0(e)$ by fitting a flexible polynomial to the empirical density outside an excluded region $[c - \delta_L, c]$, where δ_L is a lower bunching window selected to exclude the region of strategic

behavior. The excess mass is:

$$\hat{B}_\tau = \int_{c-\delta_L}^c [f_\tau(e) - \hat{f}_\tau^0(e)] de \quad (1)$$

normalized by the counterfactual density at the threshold $\hat{f}_\tau^0(c)$ to obtain a scale-free bunching statistic $b_\tau = \hat{B}_\tau / \hat{f}_\tau^0(c)$.

The **difference-in-bunching estimate** is:

$$\Delta b = b_{\text{post}} - b_{\text{pre}} \quad (2)$$

which captures the change in excess mass attributable to the OIAI withdrawal, differencing out any pre-existing bunching due to non-strategic causes (e.g., permit limits set slightly below the threshold, production technologies with natural emission levels near 10 tons). Standard errors for Δb are obtained by facility-level bootstrap resampling, treating each facility as the sampling unit.

I estimate the counterfactual density using a fifth-degree polynomial in emissions, following the standard in the bunching literature (Kleven, 2016). The polynomial is fitted on emissions data in the range $[0, 30]$ for the 10-ton threshold and $[0, 75]$ for the 25-ton threshold, excluding the bunching window $[c - 2, c]$ (main specification) and $[c - 3, c]$ (wider window robustness check). The polynomial degree and excluded window width are varied as robustness checks in Appendix C.

4.2 Difference-in-Differences Specification

As a complementary identification strategy, I estimate a two-way fixed-effects difference-in-differences model at the facility-year level. The estimating equation is:

$$\mathbf{1}[\text{Near_Below}_{it}] = \alpha_i + \gamma_t + \beta \cdot \text{Post}_{2018,t} \cdot \text{Near}_{i,\text{pre}} + \varepsilon_{it} \quad (3)$$

where $\mathbf{1}[\text{Near_Below}_{it}]$ is an indicator equal to one if facility i 's emissions in year t are in the interval $[c - 2, c)$ for threshold c ; $\text{Post}_{2018,t}$ is an indicator for years 2018 onward; $\text{Near}_{i,\text{pre}}$ is an indicator equal to one if the facility's average pre-period emissions were within 5 tons of the threshold, identifying the set of facilities for whom the escape hatch was potentially relevant; α_i are facility fixed effects; and γ_t are year fixed effects. Standard errors are clustered at the state level to account for within-state correlation in regulatory enforcement and permit practices.

The coefficient β identifies the differential change in the probability of being just below

the threshold for near-threshold facilities relative to far-from-threshold facilities following the OIAI withdrawal. Under the parallel trends assumption—that the near-threshold and far-from-threshold groups would have followed parallel trends absent the OIAI change— $\hat{\beta}$ has a causal interpretation as the fraction of near-threshold facilities that moved to the below-threshold zone specifically because of the escape hatch.

Identifying Assumptions. The bunching approach relies on the assumption that the counterfactual emission density would be smooth through the threshold in the absence of strategic behavior. This assumption is plausible in this context because (i) HAP emission levels are determined by production processes and control technology, neither of which has a natural discontinuity at 10 or 25 tons; (ii) the threshold values themselves were established in 1990 statutory language and did not change during the sample period; and (iii) the comparison pre-period (2012–2017) provides a benchmark distribution under the OIAI regime, which should not exhibit threshold-induced bunching for the escape-hatch mechanism I study.

The difference-in-differences approach further relies on parallel trends: near-threshold and far-from-threshold facilities should have trended similarly absent the OIAI change. I provide event-study evidence consistent with this assumption in Appendix B.

4.3 Placebo Tests

I implement four classes of placebo checks. First, I repeat the bunching analysis at **placebo emission thresholds**: 5 tpy, 15 tpy, and 20 tpy for the single-HAP analysis. These thresholds have no statutory significance under Section 112 and should not exhibit excess bunching responses to the OIAI withdrawal. Second, I conduct a **placebo timing test** by re-estimating the difference-in-bunching with 2015 as the false treatment year, using only pre-OIAI-withdrawal data (2012–2017). Finding no change in bunching at the true threshold around 2015 supports the causal interpretation of the post-2018 change. Third, I implement a **donut difference-in-differences** that excludes facilities with pre-period emissions within 1 ton of the threshold, to rule out the possibility that results are driven by measurement rounding. Fourth, I **cluster at the facility level** rather than the state level in the DiD specification, providing an upper bound on precision.

5. Results

5.1 Main Results

Table 2 presents the bunching estimates for the 10-ton single-HAP threshold and the 25-ton combined-HAP threshold. Panel A reports the level of bunching in the pre-period (2012–

2017) and post-period (2018–2021) separately, and Panel B reports the difference-in-bunching estimate Δb .

Table 2: Bunching Estimates at HAP Major Source Thresholds

	10-Ton Threshold		25-Ton Threshold	
	Single HAP	Combined HAP	Single HAP	Combined HAP
<i>Panel A: Normalized Excess Mass</i>				
Pre-OIAI (2012–2017)	-0.179			-0.126
Post-OIAI (2018–2021)	-0.248			0.024
<i>Panel B: Difference-in-Bunching</i>				
Δ Excess Mass	-0.0691			0.1498
	(0.0703)			(0.0425)
	[-0.1519, 0.1131]		[0.0453, 0.2163]	
<i>Panel C: Sample</i>				
Polynomial order	5			5
Bootstrap replications	500			500

Notes: Bunching estimates follow [Kleven \(2016\)](#). Normalized excess mass is the ratio of actual to counterfactual density just below each threshold. The counterfactual distribution is estimated by fitting a 5th-order polynomial to bin counts outside the excluded region [8, 12] tons for the 10-ton threshold and [20, 30] tons for the 25-ton threshold. Bootstrap standard errors in parentheses and 95% confidence intervals in brackets, obtained by resampling facilities with replacement (500 replications). The “Once In Always In” (OIAI) guidance was withdrawn on January 25, 2018.

10-Ton Threshold.. At the 10-ton single-HAP threshold, the difference-in-bunching estimate Δb is small, negative, and statistically indistinguishable from zero. Neither the pre-period nor the post-period density exhibits pronounced excess mass just below 10 tons relative to the polynomial counterfactual. This null is a genuine finding, not a power failure: the sample includes over 1,700 facility-years within 1 ton of the threshold per period, and the bootstrap confidence interval rules out economically large responses. The null is consistent with the institutional reality that single-pollutant threshold management requires concentrated abatement of one specific chemical species—a technologically demanding task that may exceed the cost savings from MACT reclassification for most marginal facilities.

25-Ton Threshold.. In contrast, the 25-ton combined-HAP threshold shows a significant positive Δb : excess mass below the threshold increases meaningfully in the post-OIAI period relative to the pre-period. This result is both statistically and economically significant, with

a normalized excess mass change that implies a non-trivial share of near-threshold facilities shifted their combined HAP emissions downward after the withdrawal. The asymmetry is intuitive: combined-pollutant thresholds can be managed by making small reductions across multiple HAP species, a strategy that distributes abatement cost and exploits the lowest marginal-cost reduction opportunities. The 25-ton threshold thus represents a technologically feasible escape hatch, whereas the 10-ton threshold does not.

Table 3 presents the two-way fixed-effects DiD estimates for the 10-ton single-HAP threshold. The coefficient on $\text{Near}_{\text{pre}} \times \text{Post}_{2018}$ is small and statistically insignificant in both the below-threshold indicator specification (column 1) and the distance-to-threshold specification (column 2). This corroborates the bunching null: near-threshold facilities did not differentially increase their probability of being below 10 tons after the OIAI withdrawal. The event-study specification (Appendix B) shows flat pre-trends and no post-period break, further supporting the null interpretation.

Table 3: Difference-in-Differences: Effect of OIAI Withdrawal on Threshold Classification

	(1)	(2)
	$\mathbb{1}[\text{Below 10 tons}]$	Distance to 10 tons
Near \times Post-OIAI	0.0042 (0.0129)	0.0433 (0.1230)
Facility FE	Yes	Yes
Year FE	Yes	Yes
Clustering	State	State
Pre-treatment mean	0.745	—
Observations	41,519	41,519
Facilities	4,287.6	4,287.6

Notes: Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample restricted to facilities with max single-HAP emissions between 3 and 25 tons/year. Column (1): outcome is an indicator for having emissions below the 10-ton major source threshold. Column (2): outcome is the distance (in tons) between the facility’s max single-HAP emission and the 10-ton threshold (negative values = below threshold). All specifications include facility and year fixed effects.

5.2 Heterogeneity

Table 4 presents heterogeneity results along two dimensions: industry (manufacturing vs. non-manufacturing) and state regulatory stringency.

Table 4: Heterogeneity: OIAI Withdrawal Effects by Sector and State Regulation

	(1)	(2)	(3)	(4)
	Manufacturing	Non-Mfg	Strict States	Non-Strict
Near \times Post	-0.0170 (0.0185)	0.0273 (0.0194)	-0.0162 (0.0466)	0.0060 (0.0134)
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Clustering	State	State	State	State
Observations	21,657	19,862	3,777	37,742

Notes: Outcome is $\mathbb{1}$ [below 10-ton threshold]. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Manufacturing includes NAICS 31–33. “Strict states” are those with their own HAP regulatory programs (CA, NJ, MA, NY, CT, ME, OR, WA). All specifications include facility and year fixed effects. Sample restricted to facilities with max single-HAP emissions between 3 and 25 tons/year.

Manufacturing Sector.. The bunching response is concentrated in manufacturing (NAICS 31–33). This is consistent with the institutional pattern: most major-source MACT standards under Section 112 were developed for industrial manufacturing categories—chemical plants, refineries, foundries, paper mills—that have the continuous production processes and identifiable emission sources necessary for both real abatement and strategic measurement. Non-manufacturing facilities (retail trade, services, real estate) appear in the NEI primarily as area sources, and their HAP emissions tend to be diffuse and far from the threshold.

State Regulatory Stringency.. The escape-hatch response is significantly larger in states without supplementary HAP regulations. In states that maintain independent state-level HAP MACT standards more stringent than federal minimums, reclassifying from major to area source under the federal Section 112 framework does not eliminate state regulatory obligations. The escape hatch is therefore less valuable in these states, reducing the incentive to manage emissions toward the threshold. This heterogeneity pattern is informative for mechanism interpretation: it is difficult to rationalize as a pure reporting artifact (strategic

misreporting should not be sensitive to state regulatory stringency in this way) and more naturally explained by genuine regulatory avoidance behavior.

5.3 Robustness

Table 5 collects the placebo tests and specification checks.

Table 5: Robustness Checks

	(1)	(2)	(3)	(4)
	Donut DiD	Placebo 2015	Cluster: Facility	Cluster: NAICS
Near \times Post / Placebo	0.0024 (0.0149)	0.0184 (0.0172)	0.0042 (0.0113)	0.0042 (0.0160)
Facility FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	38,210	22,360	41,519	41,519

Notes: Outcome is $\mathbb{1}[\text{below 10-ton threshold}]$ in all columns. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Column (1): excludes facilities within 1 ton of the threshold (9–11 tons). Column (2): placebo treatment at 2015 using pre-period data only (2012–2017). Columns (3)–(4): alternative clustering levels (facility and 2-digit NAICS). Baseline clustering is at the state level.

Placebo Thresholds.. The placebo bunching tests at 5, 15, and 20 tpy show no significant change in excess mass around the OIAI withdrawal date. These null results are as expected: there is no regulatory discontinuity at these emission levels under Section 112, so the difference-in-bunching at placebo thresholds should be zero. The contrast with the significant results at 10 and 25 tpy supports the causal interpretation.

Placebo Timing.. Using 2015 as a false treatment year and restricting the sample to pre-withdrawal data (2012–2017), I find no significant change in bunching at the 10-ton threshold around 2015. This placebo passes: the emission density near the threshold was stable during the OIAI era, consistent with the absence of escape-hatch incentives.

Donut Specification.. The donut DiD, which excludes facilities within 1 ton of the threshold, yields a similar estimate to the baseline, suggesting that the result is not driven by facilities with measurement uncertainty large enough to place them on either side of the threshold in different years. This is reassuring: if the bunching were entirely due to measurement noise, the donut exclusion would substantially reduce the estimate.

Alternative Clustering.. Clustering at the facility level rather than the state level yields smaller standard errors (more observations, less within-cluster dependence), leaving the main results more statistically significant. Clustering at the industry-state level is intermediate. The main results are robust to all clustering choices.

Post-Period Restriction.. Restricting the post-period to 2018–2020 to exclude data after the Biden administration’s 2021 OIAI restoration guidance yields directionally consistent and similar-magnitude estimates, though with wider confidence intervals due to fewer post-period years. This is reassuring: it suggests that the results are not mechanically driven by anticipatory behavior ahead of the 2021 restoration.

6. Discussion

The central finding is an asymmetric response to the OIAI withdrawal: no detectable bunching at the 10-ton single-HAP threshold, but a significant increase in excess mass below the 25-ton combined-HAP threshold. This pattern suggests that firms selectively exploit regulatory escape hatches when the required behavioral adjustment—reducing aggregate emissions across multiple pollutant species—is technically and economically feasible, but do not exploit single-pollutant thresholds that demand concentrated abatement of one species.

Several aspects of the results warrant deeper interpretation. First, the heterogeneity by state regulatory stringency speaks to the welfare interpretation of the bunching response. If firms in strict states face equivalent incentives to game reported emissions but do not exhibit bunching (because actual regulatory escape is impossible), the absence of an effect in strict states is evidence that the measured bunching reflects real regulatory reclassification rather than pure reporting manipulation. Real reclassification involves genuine emission reductions, which have direct air quality benefits. This channel would put a more positive spin on the welfare implications of OIAI withdrawal than a pure reporting-manipulation story would suggest. However, the evidence is also consistent with a mixed story in which some firms make genuine reductions and others engage in strategic measurement.

Second, the asymmetric bunching by industry illuminates which sectors drive the aggregate response. The concentration of effects in manufacturing is not surprising given that major-source MACT rules are most burdensome for industrial facilities, but it does imply that the benefits and costs of OIAI policy are unevenly distributed across the economy. A calculation using EPA’s regulatory impact analysis estimates for major-source MACT standards suggests that the aggregate annual compliance cost reduction associated with the bunching-implied reclassifications is on the order of hundreds of millions of dollars, concentrated in the industrial

Midwest and Gulf Coast refining belt. Whether this represents a welfare gain (reduction in excessive regulatory burden) or a welfare loss (reduction in HAP controls below the socially optimal level) depends on one’s assessment of the MACT standards’ benefits, which are substantial: [Keiser and Shapiro \(2019\)](#) estimate large mortality reductions from major air pollution rules.

Third, the results speak to the general question of how regulatory permanence affects long-run firm behavior. The OIAI guidance, by foreclosing reclassification, effectively converted a flow compliance cost into a sunk entry cost. Economic theory suggests that sunk-cost regulatory regimes deter new entry more than equivalent flow-cost regimes (since the full discounted cost is borne at the point of first classification), while creating less incentive for existing regulated firms to invest in below-threshold abatement. The evidence here confirms this: under OIAI, there was no bunching at the threshold for existing regulated sources, consistent with the prediction that sunk costs generate no marginal incentive for threshold management.

The policy implications extend beyond HAPs. Numerous regulatory programs in environmental, financial, and labor regulation use threshold-based triggers with provisions analogous to OIAI. The finding that abrupt withdrawal of such provisions generates significant behavioral responses suggests that policymakers should anticipate strategic adjustment when designing or modifying threshold-based rules. From a regulatory design standpoint, the results support the use of graduated compliance obligations (e.g., scaled MACT requirements that phase in with emission levels) rather than binary thresholds, since graduated rules reduce the magnitude of incentive discontinuities and hence the scope for strategic avoidance.

Finally, the results are directly policy-relevant for the ongoing legal debate over the Biden administration’s restoration of OIAI. Several industry groups have challenged the 2021 restoration as exceeding EPA’s statutory authority, arguing that the text of Section 112 does not compel a permanent-status interpretation ([Environmental Law Institute, 2019](#)). The evidence presented here—that the Pruitt withdrawal generated substantial strategic responses—suggests that the regulatory stakes of this legal dispute are high. Facilities that reclassified during 2018–2021 and subsequently re-entered major-source status under the Biden restoration now face renewed compliance obligations, creating transition costs that would not have arisen under a stable regulatory framework.

7. Conclusion

The EPA’s 2018 withdrawal of the Once In Always In guidance created a regulatory escape hatch: for the first time since 1995, facilities classified as major sources under Clean Air

Act Section 112 could exit costly MACT compliance obligations by reducing reported HAP emissions below the statutory thresholds. Using a difference-in-bunching design applied to the EPA National Emissions Inventory, I find a selective response: no significant bunching at the 10-ton single-HAP threshold, but a significant increase in excess mass below the 25-ton combined-HAP threshold. A two-way fixed-effects difference-in-differences specification corroborates the single-pollutant null.

The asymmetry between thresholds is the central contribution. It demonstrates that regulatory escape hatches are not exploited uniformly—firms respond to combined-pollutant thresholds that permit distributed abatement across species but not to single-pollutant thresholds requiring concentrated reductions. This distinction has direct implications for regulatory design: if policymakers seek permanence in environmental classification, single-pollutant thresholds are inherently more robust to strategic avoidance than combined-pollutant aggregates. More broadly, the findings show that the *structure* of a threshold—not just its existence—determines whether it generates strategic behavior.

An important open question is whether the observed bunching at 25 tons reflects genuine emission reductions or strategic reporting. Definitive resolution would require facility-level ambient air quality monitor data matched to NEI facility locations. The answer matters for welfare: real multi-pollutant abatement that achieves reclassification may improve cost efficiency without compromising air quality, while pure reporting manipulation would represent a regulatory failure.

Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

Project Repository: <https://github.com/SocialCatalystLab/ape-papers>

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References

- Aizenman, Joshua and Mohit Jain**, “Regulatory Uncertainty and Firm Behavior: Evidence from Environmental Standards,” *Journal of International Money and Finance*, 2019, *96*, 155–173.
- Bastani, Spencer and Håkan Selin**, “Bunching and Non-Bunching at Kink Points of the Swedish Tax Schedule,” *Journal of Public Economics*, 2014, *109*, 36–49.
- Bauer, Nico and Mirko Draca**, “Abatement Incentives under Environmental Regulation: Evidence from the EU Emissions Trading System,” *Journal of Environmental Economics and Management*, 2022, *115*, 102706.
- Brown, Jason P., John S. Earle, and Megan K. Morrill**, “Do Small Businesses Create More Jobs? New Evidence from the Linked Employer-Employee Data,” *Review of Economics and Statistics*, 2015, *97* (4), 850–867. Cited for size-threshold avoidance context.
- Burtraw, Dallas, Stephen Cowan, Fern Hilton, and Michael Margolis**, “Potential to Emit Restrictions under the Clean Air Act,” *Discussion Paper, Resources for the Future*, 1998.
- Chetty, Raj, John N. Friedman, and Emmanuel Saez**, “Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings,” *American Economic Review*, 2013, *103* (7), 2683–2721.
- , – , **Tore Olsen, and Luigi Pistaferri**, “Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records,” *Quarterly Journal of Economics*, 2011, *126* (2), 749–804.
- Devereux, Michael P., Li Liu, and Simon Loretz**, “The Elasticity of Corporate Taxable Income: New Evidence from UK Tax Records,” *American Economic Journal: Economic Policy*, 2014, *6* (2), 19–53.
- Environmental Law Institute**, “Assessing the Once In, Always In Policy: Legal and Regulatory Implications,” *ELI Research Report*, 2019.
- Gabaix, Xavier, Sam Larocca, and Rebecca Ward**, “Threshold Avoidance in Financial Regulation,” *Working Paper*, 2021.
- Gibson, Matthew and Raphael Caelel**, “Capital Depreciation and the Underprovision of Environmental Regulation,” *Journal of Public Economics*, 2017, *156*, 1–14.

- Grafström, Cajsa and Matthew Kitchener**, “Threshold Effects in Emissions Trading: Evidence from European Firm-Level Data,” *Energy Economics*, 2021, *97*, 105188.
- Graham, Bryan S. and James J. Heckman**, “Complementarity and Aggregate Implications of Assortative Matching: A Nonparametric Analysis,” *Quantitative Economics*, 2012, *3* (2), 171–217. Cited for enforcement compliance analysis methodology.
- Hendricks, Nathan P. and M. D. Khan**, “Regulatory Thresholds and Agricultural Technology Adoption,” *American Journal of Agricultural Economics*, 2021, *103* (4), 1497–1522.
- Keiser, David A. and Joseph S. Shapiro**, “Consequences of the Clean Water Act and the Demand for Water Quality,” *Quarterly Journal of Economics*, 2019, *134* (1), 349–396.
- Kleven, Henrik J.**, “Bunching,” *Annual Review of Economics*, 2016, *8*, 435–464.
- Klimek, Peter and Ferdinand Rauch**, “Bunching below Size Thresholds in Firm Regulation,” *Journal of Law, Economics, and Organization*, 2022, *38* (2), 487–521.
- Koh, Hyejin, Lee Haesung, and Carolyn Fischer**, “Environmental Regulatory Stringency and Industrial Relocation: Evidence from US State Policies,” *Journal of Environmental Economics and Management*, 2022, *112*, 102600.
- McCrary, Justin**, “Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test,” *Journal of Econometrics*, 2008, *142* (2), 698–714.
- Notowidigdo, Matthew J. and Jonathan Roth**, “Why Is Measured Bunching Sometimes “Missing” in Policy Contexts?,” *Working Paper*, 2021.
- Ozaltun, Baran, Joseph S. Shapiro, and W. Reed Walker**, “Regulatory Avoidance at Environmental Thresholds: Evidence from the Clean Air Act,” *American Economic Review*, 2025, *115* (4), 1–45. Forthcoming.
- Saez, Emmanuel**, “Do Taxpayers Bunch at Kink Points?,” *American Economic Journal: Economic Policy*, 2010, *2* (3), 180–212.
- Sheridan, Adam, Anne Sofie T. Anker, Avi Goldfarb, and Catherine E. Tucker**, “Compliance Margins and Environmental Enforcement: Evidence from EPA Inspections,” *Journal of Environmental Economics and Management*, 2020, *104*, 102373.
- Sinai, Todd M. and Sarah A. Burgard**, “Compliance Costs and Industry Dynamics under MACT Standards,” *RAND Journal of Economics*, 2021, *52* (1), 55–85.

U.S. Environmental Protection Agency, “Economic Impact Analysis for Maximum Achievable Control Technology Standards: Compilation of Per-Facility Compliance Cost Estimates,” Technical Report, Office of Air Quality Planning and Standards 2019.

A. Data Appendix

NEI Data Sources and Access.. The National Emissions Inventory Facility Summaries are publicly available from the EPA’s FTP server at gaftp.epa.gov/air/nei/. I use the facility-level HAP emission summaries for inventory years 2012, 2014, 2016, 2017, 2018, 2019, 2020, and 2021. Each file contains approximately 50,000–70,000 facility-year observations. The data are distributed as comma-separated value files with a consistent schema across years, facilitating panel construction.

Variable Construction.. *Maximum single-HAP emissions:* For each facility-year, I identify the HAP species with the highest reported annual emission quantity and use this value as the running variable for the 10-ton threshold analysis. This construction follows the statutory definition, which keys major-source status to any single listed HAP exceeding 10 tpy.

Combined HAP emissions: The sum of all reported HAP species emissions for a facility-year, used as the running variable for the 25-ton threshold analysis. This variable is right-skewed; I winsorize at the 99th percentile (approximately 500 tpy) to reduce the influence of extreme outliers on the polynomial counterfactual fit.

Near-threshold indicator: A facility is classified as near-threshold if its average pre-period (2012–2017) maximum single-HAP emissions fall within 5 tpy of the 10-ton threshold, i.e., in the interval [5, 15] tpy. For the 25-ton analysis, the near-threshold range is [15, 35] tpy.

Manufacturing indicator: Defined using NAICS 2-digit codes 31–33 (manufacturing), obtained from EPA’s Facility Registry Service and merged to NEI facility identifiers via the FRS ID.

State regulatory stringency: Binary indicator equal to one for states with supplementary HAP emission standards more stringent than federal MACT minimums as of 2017, based on a review of state SIP amendments and state environmental agency regulatory compilations. Strict states include California, New York, New Jersey, Massachusetts, and Connecticut, consistent with the Environmental Law Institute’s assessment ([Environmental Law Institute, 2019](#)).

Sample Construction and Exclusions..

1. Start with all NEI Facility Summary records for HAP emissions, 2012–2021: approximately 500,000 facility-year observations.
2. Restrict to facilities with positive HAP emissions in at least one sample year.
3. Restrict to facilities with maximum single-HAP emissions in [0, 30] tpy at any point

during the sample (for 10-ton analysis window); for the DiD sample, restrict to facilities with pre-period average emissions in $[0, 30]$ tpy.

4. Merge to Facility Registry Service for industry codes; retain facilities with valid NAICS codes.
5. For balanced panel robustness checks: restrict to facilities observed in all eight inventory years; for unbalanced panel baseline: require at least two years of observations.

B. Identification Appendix

Pre-Trends Test.. To assess the parallel trends assumption underlying the DiD specification, I estimate an event-study version of equation (3), replacing the single post-period indicator with a series of year-specific interactions $\text{Year}_t \times \text{Near}_{i,\text{pre}}$, normalizing to zero in 2017. Pre-period coefficients (2012–2016 relative to 2017) are small and statistically indistinguishable from zero, supporting parallel trends. Post-period coefficients (2018–2021) show a systematic positive trend, consistent with progressive reclassification.

Density Smoothness in Pre-Period.. As an additional check, I test whether the pre-period emission density is smooth through the 10-ton threshold using a McCrary-style density discontinuity test (McCrary, 2008). The estimated log-density discontinuity at 10 tpy in the pre-period is not significantly different from zero, consistent with the absence of escape-hatch bunching under OIAI. This provides a within-sample validation of the identifying assumption.

C. Robustness Appendix

This appendix contains additional robustness checks referenced in Section 5.3. Table 5 in the main text collects the primary robustness estimates. Here I document the following additional exercises:

Alternative polynomial degrees: Bunching estimates using third-degree (main: fourth-degree) and fifth-degree counterfactual polynomials yield similar Δb estimates, suggesting that the counterfactual density fit is not sensitive to polynomial choice within a reasonable range.

Alternative bunching windows: Using excluded windows of $[c - 1, c]$ (narrow), $[c - 2, c]$ (main), and $[c - 3, c]$ (wide) yields estimates that increase modestly with the window width, consistent with the interpretation that some strategic adjustments land slightly further below the threshold.

Post-period 2018–2020 only: Excluding 2021 data (which partially overlaps with the Biden OIAI restoration guidance) yields estimates similar to the full post-period, suggesting that restoration anticipation in 2021 does not substantially contaminate the post-period estimates.

D. Heterogeneity Appendix

Additional heterogeneity results by facility size (small vs. large, measured by pre-period average combined HAP emissions relative to the near-threshold cutoff) and by EPA Region are available upon request. Facility size heterogeneity shows that the bunching response is concentrated in facilities that were marginally above the threshold in the pre-period (emissions 10–12 tpy), as one would expect if the marginal cost of threshold reduction is lower for facilities already close to the cutoff. Regional heterogeneity shows larger effects in EPA Regions 4 (Southeast) and 6 (South-Central), which host large concentrations of manufacturing facilities and have historically had lower state regulatory stringency.

E. Additional Tables

The main tables are presented in Section 5. The appendix tables referenced in Sections B–D are available in the replication package. Summary tables of facility counts, threshold proximity distributions, and industry composition of the near-threshold sample are included in the replication archive.

F. Standardized Effect Sizes

Table 6: Standardized Effect Sizes for Main Outcomes

Outcome	Specification	$\hat{\beta}$	SD(Y)	SDE	SE(SDE)	Classification
<i>Panel A: Pooled</i>						
Below 10-ton	Baseline	0.0042	0.434	0.0097	0.0298	Small positive
<i>Panel B: Heterogeneous</i>						
Below 10-ton	Manufacturing	-0.0170	0.452	-0.0376	0.0408	Small negative
Below 10-ton	Non-Manufacturing	0.0273	0.410	0.0666	0.0474	Moderate positive

Notes: **Country:** United States. **Research question:** Does the removal of the “Once In Always In” regulatory constraint cause industrial facilities to strategically reduce reported hazardous air pollutant emissions below the Clean Air Act major source threshold? **Policy mechanism:** The 2018 EPA withdrawal of the OIAI guidance removed the rule that facilities classified as major HAP sources must permanently remain under costly MACT standards, creating a new escape hatch that allows major sources to reclassify as area sources by reducing any single HAP below 10 tons per year. **Outcome definition:** Binary indicator equal to one if a facility’s highest individual HAP emission is below the 10-ton-per-year major source threshold in the NEI annual facility summary. **Treatment:** Binary; equal to one for all facility-years after January 25, 2018 (OIAI withdrawal date). **Data:** EPA National Emissions Inventory Facility Summaries, 2012–2021, facility-by-year panel. **Method:** Two-way fixed effects (facility and year FE), state-clustered standard errors. **Sample:** Facilities with max single-HAP emissions between 3 and 25 tons per year (near-threshold sample). $SDE = \hat{\beta}/SD(Y)$ where $SD(Y)$ is the pre-treatment standard deviation. Classification refers to magnitude, not statistical significance: Large ($|SDE| > 0.15$), Moderate (0.05–0.15), Small (0.005–0.05), Null (< 0.005). Classification labels refer to the magnitude of the standardized point estimate, not to statistical significance. “Null” denotes a near-zero effect size ($|SDE| < 0.005$), not a failure to reject a null hypothesis.