Strategic Local Regulators and the Efficacy of Uniform Pollution Standards

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December 27, 2021

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Abstract

We assess the effect of changes in a national pollution standard on local pollution. Local jurisdictions allocate resources in regulating pollution at the local level, and in areas with high pollution, local regulators have an incentive to strategically violate the national pollution standard and allocate fewer resources to regulating pollution locally in response to a more stringent national pollution standard. Our empirical analysis of the 2006 revision of the 24-hour $PM_{2.5}$ national standard provides evidence that supports this theory, showing that both monitor readings and individual plant emissions did not decrease or even increased in areas that intentionally violate the national standard.

Key words: Strategic Response, Local Pollution, National Ambient Air Quality Standard (NAAQS), Clean Air Act (CAA), Non-attainment, $PM_{2.5}$

JEL codes: H11, H51, H75, Q52, Q53, Q58

1 Introduction

Air quality in the United States is regulated under the Clean Air Act. Under this Act, the federal EPA is required to set the National Ambient Air Quality Standards (NAAQS) and determine the attainment status of all counties across the country. A county is designated as being in "*non-attainment*" if local monitor readings exceed the NAAQS.[1]. A non-attainment designation leads to more stringent federal regulation including new source review (Greenstone, 2002) and the requirement to develop county/state implementation plans outlining how areas will reduce air pollution. Past work has documented the economic cost of a non-attainment designation, including a loss in job opportunities and declines in capital stock and output (Greenstone, 2002). Therefore, local regulators have an incentive to avoid a non-attainment designation for their counties (Grainger et al., 2020). We hypothesize that local regulators allocate resources strategically, with the objective of regulating local pollution so that the cost of regulation is appropriately balanced against the risk of being designated as being in non-attainment.

[1] A county is designated as being in violation of the NAAQS if the 98th percentile value of air pollution concentration measured by monitors exceeds the 24-hour pollution standard more than once per year over a three-year period, or the three-year average annual arithmetic mean pollution concentration measured by the monitors exceeds the annual standard.

Strategic behavior by local regulators has been noted by the previous literature. For example, Auffhammer et al. (2009) find that after a county is designated as a "*non-attainment county*", a detectable change in the concentration of the corresponding pollutant can only be found at monitors whose readings violate the national standard (violating monitors). Gibson (2019) observed that as the distance between a plant and a violating monitor increases, the magnitude of the negative treatment effect of the "*non-attainment county*" designation on individual plant emissions declines. Grainger et al. (2020) find that local regulators strategically choose less polluting locations for new monitors to avoid a non-attainment reading. Zou (2021) found that, consistent with the EPA's one-in-six day monitoring schedule for $PM_{2.5}$ pollution, local regulators strategically issue "Action Day" calls urging citizens to improve air quality by "taking actions" such as reducing energy and automobile use, leading to lower $PM_{2.5}$ concentration on days when the monitors are operating. Mu et al. (2021) find that local regulators are more likely to shutdown monitors during more polluted days.

Drawing from these observations, we present a formal model to describe a local regulator's strategic behavior in allocating resources to control local pollution. We assume that local pollution concentrations can be predicted, albeit with error, by multiple local factors, such as emissions from local industry and from other local unregulated economic activities. We assume that the random prediction error, which has a zero mean, arises due to unobserved local activities. The local regulator chooses plant-specific regulation resources, where more regulation resources generate greater regulation pressure and thus indirectly lower plant emissions through the plant's own cost minimization process on emissions and abatement. When choosing plant-specific regulation resources, the regulator balances the benefits and costs of plant emissions: the benefit of emissions is the savings in regulation resources; the cost of emissions is the damage to public health plus the expected penalties associated with the risk of receiving a non-attainment designation when local monitor readings exceed the NAAQS. We assume that the expected violation penalty depends on the probability that the monitor reading exceeds the pollution standard. For each plant, the local regulator determines the optimal plant-specific regulation resources and the associated plant emissions, such that the marginal benefit equals the marginal cost.

Under fairly general and innocuous assumptions on the slope of the marginal benefit/cost functions, our model suggests that the local regulator's optimization problem may have multiple solutions, implying heterogeneity in the local regulator's response to changes in the national standard. For areas with few polluting industries, a relatively small amount of regulation resources is needed to maintain local pollution at a low level, and allowing more local emissions saves little regulation cost. Therefore, the marginal benefit of emissions is low and the local regulator aims to comply with the national standard to avoid violation penalty. In practice, the local regulators allocate regulation resources such that local monitor readings are expected to be lower than the national standard, and we call these monitors "expected compliant monitors". In these areas, an increase in the stringency of the national standard raises the marginal cost of emissions by increasing the probability of violation, and therefore motivates the local regulators to allocate more resources to regulating pollution. Local plants react to the associated increase in regulation pressure by lowering their emissions, and local pollution also decreases. However, local regulators in areas with a great many polluting industries may behave quite differently, since more regulation resources are needed to lower pollution, and allowing more local emissions saves a relatively large amount of regulation cost. The marginal benefit of emissions in these areas is high so that the local regulators have an incentive to allow higher emissions. It is even possible that the local regulators find the national standard too expensive to comply with, so that they would rather choose high risk and expected penalty of violating the national standard. In practice, these regulators allocate resources such that the readings at local monitors are expected to be higher than the national standard, and we call these monitors "expected violating monitors". In these areas, an increase in the stringency of the national standard makes it even more expensive to comply with, which further motivates the local regulators to allocate fewer regulation resources. Local plants react to the decrease in regulation pressure by increasing their emissions, and the readings at local "expected violating monitors" also increase.

To test the empirical predictions of our theory, we focus on the 2006 revision of the 24-hour NAAQS for $PM_{2.5}$, which was reduced significantly from 65 $\mu g/m^3$ to 35 $\mu g/m^3$. We hypothesize that, in contrast to popular expectations, this revision led to an increase in readings at "expected violating monitors", as well as in air emissions from local plants around them. Following Greenstone (2003) and Gibson (2019), we construct monitor-by-year and plant-by-year data sets by combining several data sources including the EPA's AQS (monitor data), TRI (plant data), ECHO (inspection and violation data), Greenbook (county non-attainment status) and Census data (county/census tract socio-economic characteristics). We compare the average annual $PM_{2.5}$ readings and particulate matter emissions of surrounding TRI plants at "expected violating monitors" and at "expected compliant monitors". We find that, consistent with our theory, there is a significant increase in both $PM_{2.5}$ readings and particulate matter emissions of surrounding plants at "expected violating monitors" after the NAAQS was revised downwards.

2 Theoretical Framework

In this section, we propose a theoretical framework to describe a pollution regulation scheme that is widely used in U.S., in which the federal government sets a universal pollution standard for the entire country and penalizes local areas that violate the national standard. Our model describes the local regulator's strategic behavior in allocating pollution regulation resources in response to changes in the national standard.

2.1 Ground-based Air Pollution Monitors

Our theoretical framework follows the spirit of Rabassa (2008) and Grainger et al. (2020). The federal government determines whether local areas violate the existing national pollution standard based on ground-based pollution monitor readings. If the local monitor readings exceed the national standard, then the area is subject to violation penalties. The local regulator strategically allocates regulation resources to balance cost of regulation, pollution damage, and expected penalties that are associated with the risk of violating the national standard.

Ground-based pollution monitors measure air pollution in the immediate vicinity of monitors, which in turn depends on the air pollution generated from both local industries and other unregulated economic activity in the neighborhood (for example, traffic and residential/commercial fuel combustion). Let J be the number of monitors in a local regulator's jurisdiction. Since each monitor detects air pollution in its immediate vicinity, we define I_j as the set of plants that are located within the area that is covered by monitor j. Due to the sparsity of monitor locations in the United States and for model simplicity, we assume that I_j's are mutually exclusive, so that there is at most one unique monitor that captures the emissions from all local plants.[2] For plant $i \in I_j$, let d_{ij} be the distance between plant i and the monitor j that covers the area, e_i be plant i's emissions, and m_j be monitor j's reading. $f(d_{ij})$ is the function that maps emissions from plant i to the concentration detected by monitor j based on the distance d_{ij}.[3] Monitor reading m_j can be written as

$$m_j = \beta X_j + \sum_{i \in I_j} f(d_{ij}) e_i + u_j, \tag{1}$$

where X_j is a vector of local socio-economic characteristics that determine the background air pollution from other unregulated economic activities. $\sum_{i \in I_j} f(d_{ij}) e_i$ is the aggregate pollution captured by monitor j that comes from all the plants located within the area covered by monitor j. u_j is a random residual; we assume $u_j \sim N(0, \sigma^2)$, so that the expected monitor reading, M_j, is

$$M_j = \beta X_j + \sum_{i \in I_j} f(d_{ij}) e_i. \tag{2}$$

The information provided by the monitor readings is used by the local regulator to allocate resources to regulate pollution locally, and by the federal government to determine whether the local jurisdiction is compliant with the national standard.

2.2 Local Regulator's Problem

Although the local regulator has little or no control over emissions from unregulated economic activities and therefore the random residual in the monitor reading function (Equation 1), she can allocate resources to regulate local point sources such as manufacturing plants within her

[2] In practice, if a plant is located in the area covered by multiple monitors, then these monitors are close to each other and measure the air pollution of similar areas. These monitors are expected to have similar readings so that we treat them as a single monitor.

[3] Empirically, we simplify the function by arbitrarily choosing a threshold distance d_0 such that $f(d_{ij}) = \gamma$ if $d_{ij} < d_0$ and $f(d_{ij}) = 0$ otherwise, where γ is a positive constant. In a more sophisticated setting, one may assume that $f(d_{ij})$ is a monotonically decreasing, continuous or non-parametric function of d_{ij}.

jurisdiction. More regulation resources generate higher regulation pressure, which lowers plant emissions. Therefore, the local regulator chooses the optimal level of regulation resources for every plant $i \in I_j$ that is located in the area covered by monitor j within its jurisdiction to minimize the total expected cost of pollution, which includes the cost of allocated regulation resources, local pollution damage (such as public health damage and the loss in local housing values), and the expected violation penalties that are associated with the risk of violating the national standard.

We define an indirect regulation cost function, $C(e_i;\theta_i)$, as the cost of allocated regulation resources that are required for maintaining plant i's emission level at e_i. θ_i is a vector of plant characteristics. The local regulator allocates regulation resources to plant i and generates pressure on the plant to lower its emissions. The plant receives and quantifies the regulation pressure as its own marginal cost of emissions, and determines its optimal emissions e_i by balancing the plant marginal abatement cost (depending on θ_i) against the plant marginal emission cost. $C(e_i;\theta_i)$ captures the one-to-one monotonic mapping between plant optimal emissions e_i and plant-specific cost of regulation resources allocated by the local regulator at plant i, conditional on plant characteristics θ_i (*we don't need more assumptions in this mapping*). With such a one-to-one mapping, the local regulator indirectly chooses plant emissions e_i when she allocates plant-specific regulation resources. With the intuition that higher plant emissions require less regulation resources and cost; and that at a higher emission level, fewer regulation resources are saved when allowing a marginal increase in plant emissions, we have $\frac{\partial C(e_i;\theta_i)}{\partial e_i} < 0$, $\frac{\partial^2 C(e_i;\theta_i)}{\partial e_i^2} > 0$. Appendix A.1 and Appendix Figure 9 describe the details of the indirect regulation cost function.

We assume the local regulator estimates local pollution damage $G\big(M_j;\sigma_j\big)$ based on M_j, the expected pollution concentration recorded at monitor j, and a vector of local socio-economic characteristics σ_j in the neighborhood of that monitor; higher concentrations of pollution cause greater damage; and the marginal damage increases in pollution concentrations. Accordingly, we have $\frac{\partial G\left(M_j;\sigma_j\right)}{\partial M_j} > 0$, and $\frac{\partial^2 G\left(M_j;\sigma_j\right)}{\partial M_j^2} > 0$. In fact, the local regulator considers the health damage across the whole jurisdiction, not just in the vicinity of monitor j. We assume that local pollution damage is additive across monitors. Therefore, when considering the resources to allocate at a particular monitor j, the local regulator does not need to worry about the pollution damage at other monitors.

In addition, we assume that the expected violation penalty equals the probability of local concentrations exceeding the national standard times a fixed and exogenously specified violation penalty.[4] Let the national standard be s, and the fixed violation penalty be K (regardless of the magnitude of violation). Recall that m_j is uncertain due to a random residual u_j, so the expected violating penalties can be written as $(1 - Pr(m_j \leq s))K$, where $Pr(m_j \leq s)$ is the probability that the concentration m_j is less than or equal to the national standard s (probability of compliance/not violating). Finally, with the intuition that by choosing plant-specific regulation resources the local regulator can indirectly choose plant emissions, her problem for each monitor j within the jurisdiction becomes:[5]

$$\begin{aligned}
&\min_{e_i|i \in I_j} \sum_{i \in I_j} C(e_i;\theta_i) + G\big(M_j;\sigma_j\big) + \Big(1 - Pr(m_j \leq s)\Big)K \\
&\quad = \sum_{i \in I_j} C(e_i,\theta_i) + G\big(\beta X_j + \sum_{i \in I_j} f(d_{ij})e_i;\sigma_j\big) + \Big(1 - Pr(\beta X_j + \sum_{i \in I_j} f(d_{ij})e_i + u_j \leq s)\Big)K.
\end{aligned} \tag{3}$$

To solve the problem, we have the following first order condition for each plant ι in I_j (when $i = \iota$):

$$\underbrace{-C'(e_\iota;\theta_\iota) - G'(M_j;\sigma_j)f(d_{\iota j})}_{\text{marginal net benefit of } e_\iota} = \overbrace{\psi\Big(s - \beta X_j - \sum_i f(d_{ij})e_i\Big)f(d_{ij})K}^{\text{marginal penalty cost of } e_\iota}, \tag{4}$$

where $C'(e_\iota;\theta_\iota) = \frac{\partial C(e_\iota;\theta_\iota)}{\partial e_\iota}$ and $G'(M_i;\sigma_j) = \frac{\partial G(M_j;\sigma_j)}{\partial M_j}$. $\psi(\cdot)$ is the probability density of the random residual u_j. The left hand side of equation 4 is the marginal net benefit of plant ι's emissions, defined as the marginal savings in regulation resources on plant ι minus the marginal local pollution damage, and the right hand side is the marginal cost of plant ι's emissions measured by the marginal increase in expected violation penalties. Since u_j follows a normal distribution,

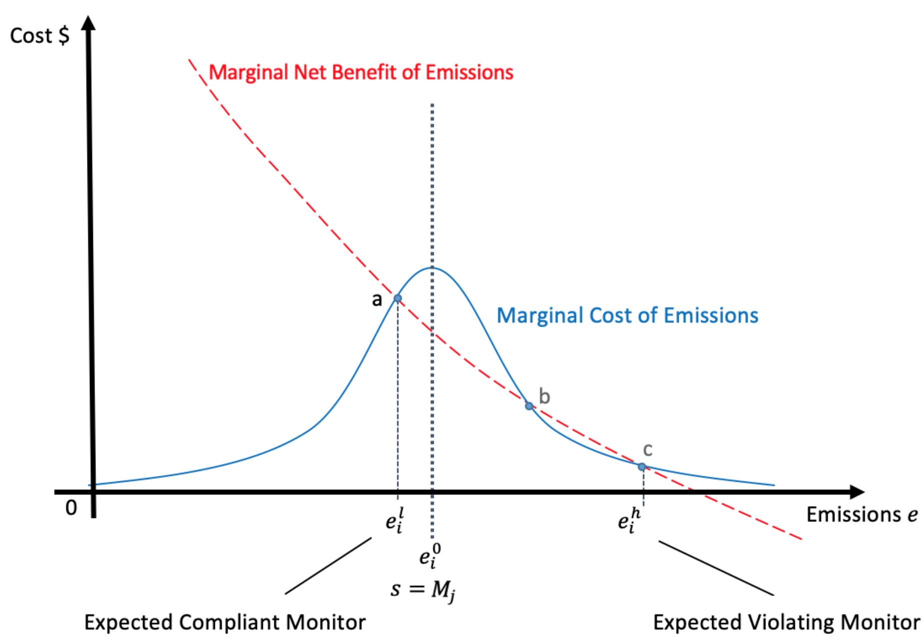
[4] In practice, EPA defines 3 non-attainment classifications based on the magnitude of violation for PM pollution: "moderate", "serious", and "serious and fail to attain". The punishment, in terms of the length and required elements of state implementation plans, increase by the levels of classification (see https://www.epa.gov/pm-pollution/particulate-matter-pm-nonattainment-area-sip-requirements). The punishment varies categorically, and here we simplify such variation to binary without loss of generality.

[5] We assume that the local regulator acts like a benevolent social planner and seeks to maximize local social welfare by internalizing pollution damages. However, it is also possible that the regulator has a more limited objective of minimizing the direct cost of pollution reduction which does not account for pollution damages. Our qualitative model structure and results hold under either objective function.

$\psi(\cdot)$ is a symmetric probability density function with $N(0, \sigma^2)$.[6]

According to equation 4, for any plant $i \in I_j$ with $f(d_{ij}) > 0$, the first order condition may have at most three solutions; the number of solutions depends on the relative slope and curvature of marginal benefit and cost curves.[7] Figure 1 illustrates an example with three solutions, labelled by a, b and c. Among these solutions, points a and c are local minima, whereas solution b is a local maximum.[8] By choosing the optimal regulation resources for plant i, the local regulator indirectly chooses plant i's emissions at the global minimum e_i^*, which is either at a (low optimal emissions, $e_i^* = e_i^l$) or c (high optimal emissions, $e_i^* = e_i^h$).

Figure 1: Three F.O.C Solutions



With the pollution of all other plants given, the marginal cost curve of plant i's emissions is symmetric with respect to e_i^0, the emission level at which the expected reading of the local monitor equals the national standard.[9] If the local regulator's optimal solution is at point a, i.e., in the

[6]The model is flexible to other distribution assumptions, as long as the distribution is symmetric with respect to zero.

[7]For plants far away from monitor j so that $f(d_{ij}) = 0$, there is unique optimal solution, where $\frac{\partial C(e_i, \theta_i)}{\partial e_i} = -G'(M_j; \sigma_{ij}) f(d_{ij})$. This solution suggests that the emissions of these plants are irrelevant to the readings at monitor j and therefore to the local regulator's strategic behavior.

[8]See detailed proof in Online Appendix A.2. Figure 10 in the appendix illustrates the other four possible cases for the solutions of the first order condition.

[9]e_i^0 is the emission level that satisfies the following condition: $s = M_j = \beta X_j + [\sum_{\iota \in I_j, \iota \neq i} f(d_{\iota j}) e_\iota + f(d_{ij}) e_{ij}^0]$.

left half of marginal cost curve, and plant emissions e_i^l are lower than e_i^0, then the expected local monitor reading is lower than the national standard. Conversely, if the local regulator's optimal solution is at point c (right half of marginal cost curve) and plant emissions e_i^h are higher than e_i^0, then the expected local monitor reading becomes higher than the national standard. This implies that while choosing plant-specific regulation resources, the local regulator also determines whether expected monitor readings comply with or violate the national standard. In other words, if the cost of local pollution control is relatively low, then it is optimal for the local regulator to allocate sufficient resources to regulating local pollution so that the expected monitor readings are in compliance with the national standard. In this case we call the pollution monitor an "expected compliant monitor". On the other hand, if the cost of complying with the national standard is high, then the regulator allocates regulation resources such that it is optimal to intentionally violate the national standard; we refer to such monitors as "expected violating monitors".[10]

More generally, whether a monitor is an "expected violating monitor" or not depends on whether the optimal point locates in the right or left half of the marginal cost curve. Among all the other cases described in Appendix Figures 10, "expected compliant monitors" exist when the marginal net benefit of emissions is relatively flatter/lower (so that it crosses the the left half of the marginal cost curve). These are likely to be areas with relatively fewer polluting industries (so regulating local pollution is less costly) or where pollution may cause greater damage. "Expected violating monitors" exist when the marginal net benefit of emissions is relatively steeper/higher (so that it is steeper than the marginal cost curve when they cross at the right half), referring to areas with relatively more polluting industries (so regulating local pollution is more costly) or where pollution may cause lower damage.

[10]If a monitor is determined to be an "expected compliant monitor", then the optimal emissions of all plants in the area covered by the monitor are always located in the left half of the symmetric bell-shape marginal cost curve ($e_i^* \leq e_i^0$). If a monitor is an "expected violating monitor", then the optimal emissions of all plants covered by the monitor are always in the right half of the symmetric bell-shape marginal cost curve ($e_i^* > e_i^0$). This conclusion can be easily derived from Lemma 2 in Appendix A.3.

2.3 The National Standard

The universal national standard plays a crucial role in determining the local regulator's strategic response because it determines the marginal cost of emissions through the probability of violating the national standard and the associated expected violation penalty. Consider the case where the federal government lowers the national standard (decreases the value of s), with the expectation that a more stringent standard will encourage local regulators to devote more resources to regulating local pollution sources and improving local air quality. However, our theory shows differently: a more stringent national standard has heterogeneous effects across jurisdictions. For areas covered by "expected compliant monitors", a more stringent national standard incentivizes local regulators to increases the resources allocated to pollution regulation and improves local air quality; whereas the opposite occurs in areas where local regulators intentionally violate the national standard.

Figure 2: Local Regulator's Behavior under A More Stringent National Air Pollution Standard

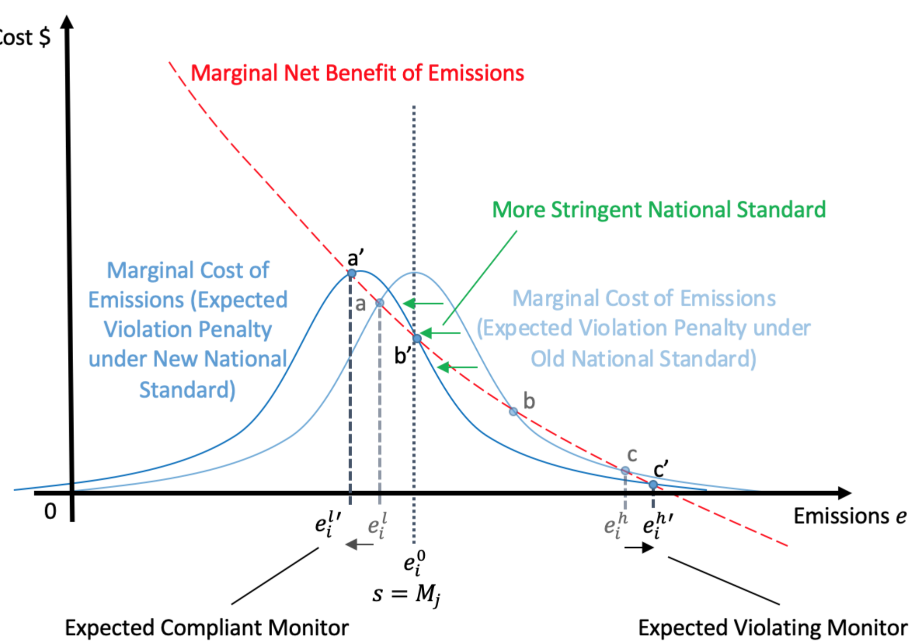


Figure 2 illustrates how local regulators respond to a revision of the national standard which decreases the value of s and shifts the marginal cost curve of emissions parallelly to the left.[11] Recall

[11] The marginal net benefit curve does not change because, according to equation 4, it is not relevant to the national standard.

that, prior to the revision, local regulators in areas covered by "expected compliant monitors" are incentivized to allocate sufficient resources to regulating local pollution sources such that optimal emissions of plant i are at e_i^l. When the marginal cost curve shifts to the left, the optimal solution shifts from a to a'. Since a' also falls in the left half of the probability distribution for the marginal cost of emissions, the local regulator is further incentivized to increase regulation resources so that individual plant emissions decrease to $e_i^{l\prime}$. With lower plant emissions local air quality improves. On the other hand, in the areas covered by "expected violating monitors", where prior to the revision local regulators intentionally violate the national standard and optimal emissions for plant i are at e_i^h, the leftward shift of the marginal cost curve shifts causes the optimal solution to shift from c to c'. This implies that the local regulator further decreases regulation resources so that individual plant emissions increase to $e_i^{h\prime}$ and local air quality worsens. This result holds for the all the other cases shown in appendix Figure 10. Accordingly, we have the following empirically testable proposition:

Proposition: A more stringent national standard decreases emissions in areas covered by "expected compliant monitors" but increases emissions in areas covered by "expected violating monitors".[12]

This proposition describes heterogeneous effects that can also been explained intuitively. In areas covered by "expected compliant monitors", a more stringent national standard increases the marginal cost of emissions (marginal expected violation penalties), which encourages the local regulator to allocate more resources and reduce more local emissions. However, for the areas covered by "expected violating monitors", where the local regulator has found that the previous national standard was already too expensive to comply with, lowering the national standards makes the compliance even more expensive. In these areas, after the revision, a marginal decrease in local emissions reduces less probability of violation and the expected violation penalties than before. In another words, a marginal increase in local emissions increase less expected violation penalties thus

[12]See proof in Appendix A.3.

the marginal cost of emissions (marginal expected violation penalties) decreases. Therefore, the local regulator allocates even fewer resources to pollution regulation after the revision resulting in higher local emissions.

3 Data

To empirically test the proposition associated with our theory, we analyze the effects of the U.S. EPA's 2006 revision of the $PM_{2.5}$ NAAQS. On January 17th, 2006, the EPA proposed lowering the national $PM_{2.5}$ 24-hour standard from $65\mu g/m^3$ to $35\mu g/m^3$ (this standard is for the 98% quantile of the three-year average of 24-hour $PM_{2.5}$). The new standard went into efffect on October 17, 2006 (https://www.epa.gov/pm-pollution/2006-national-ambient-air-quality-standards-naaqs-particulate-matter-pm25). We study the impact of this revision on local air pollution by comparing both monitor and plant emission data before and after the revision.[13] Our datasets combine several sources, including AQS (monitor data), TRI (plant data), ECHO (inspection and violation data), and the Greenbook (county non-attainment status) databases provided by the EPA; along with Census data (county/census tract socio-economic characteristics). Our study period begins in 2002, five years after the previous 1997 revision of the $PM_{2.5}$ standard (to avoid lagged effects), and ends in 2011, one year before the next revision.[14]

3.1 Monitor-by-Year Data

There are in total 1,937 active and EPA approved $PM_{2.5}$ monitors in the contiguous United States from 2002 to 2011. Among these 1,457 monitors measured $PM_{2.5}$ concentration using the reference of "$PM_{2.5}$ 24-hour 2006" standard and were not affected by an "exceptional event", so that their

[13] Although the non-attainment designation process under the 2006 $PM_{2.5}$ revision started from November 2007 (see https://www.epa.gov/sites/default/files/2016-04/documents/20060921_standards_factsheet.pdf, page 5), we assume that local regulators change their local regulation strategies as soon as the revision was proposed in early 2006.

[14] We focus on 2006 revision because of the lack of socio-economic data at the time of the previous revision and because the 2012 revision was relatively minor, changing the primary $PM_{2.5}$ standard from $15\mu g/m^3$ to $12\mu g/m^3$.

measurements can be used to determine non-attainment designation.[15] Since monitor location can be endogenously selected and new monitors are likely to be placed at high pollution areas (Grainger et al., 2020), we exclude monitors that are only temporarily active before/after the revision. Therefore, our sample consists of 994 monitors that are active at least 1 year before and 1 year after (including) 2006 (the revision year).[16]

Consistent with our theoretical framework, we separate monitors into two groups, "expected compliant monitors" and "expected violating monitors", with respect to the 2006 revised $PM_{2.5}$ standard. Due to the fact that monitor readings are random values and "expected violating monitors" have a large probability of violating the national standard (the emissions at "expected violating monitors" are usually at the far right tail of the normal distribution, see Figure 1), we define a monitor as an "expected violating monitor" if its observed daily $PM_{2.5}$ readings exceeded the national standard every year after the 2006 revision (i.e., between 2006 and 2011). Otherwise, the monitor is defined as an "expected compliant monitor". In the final monitor-by-year dataset, there are 128 "expected violating monitors" and 866 are "expected compliant monitors".[17] Figure 3 shows the location of the monitors in our sample along with the counties that had ever been designated as "non-attainment" between 2006 and 2011. Not surprisingly, "expected violating monitors" are more likely to be in the $PM_{2.5}$ non-attainment counties.

In Figure 4, we compare the average annual trend of $PM_{2.5}$ readings between "expected violating monitors" and "expected compliant monitors". The figure shows that the trend began to diverge from 2006 onward, with a dramatic increase in $PM_{2.5}$ concentration at "expected violating monitors".

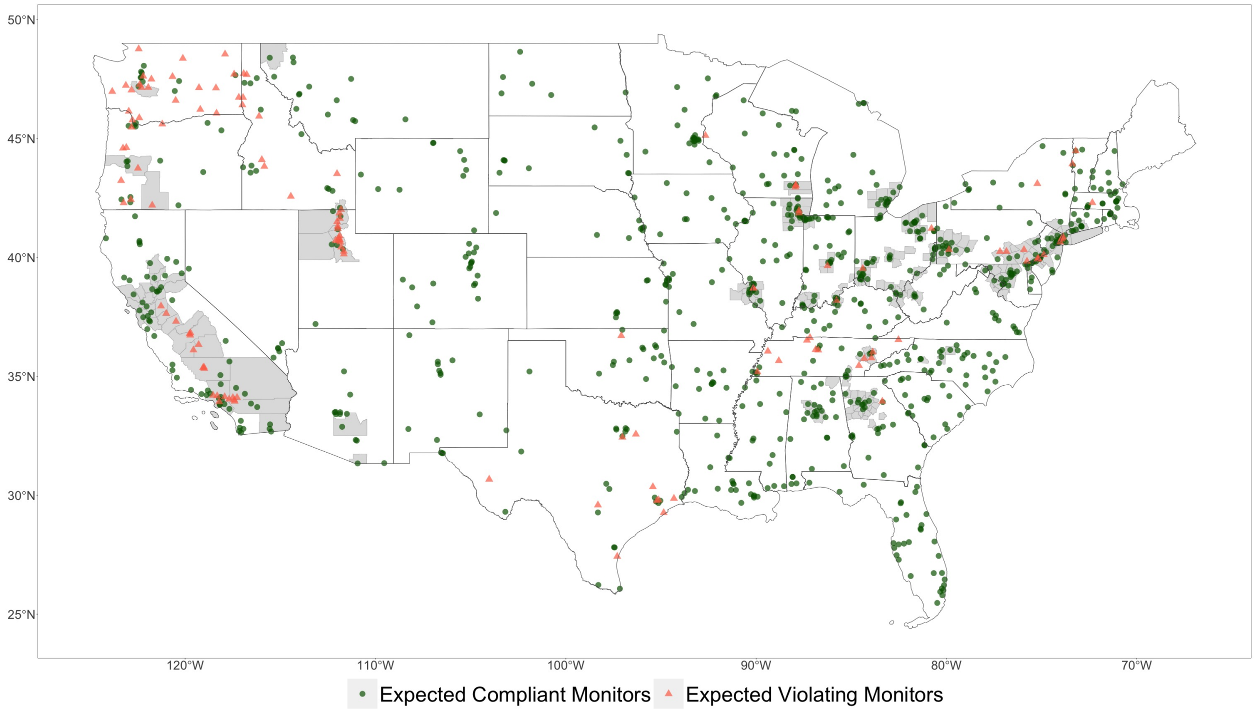
We obtain annual socio-economic data from the U.S. Bureau of Economic Analysis at the county

[15] See https://aqs.epa.gov/aqsweb/airdata/FileFormats.html for how EPA aggregates the data and local compliance status under different revisions of NAAQS. Exceptional events are defined in "The Exceptional Event Rule" (EER). "The EER allows the ambient air quality data which is submitted to AQS and used in making regulatory decisions, to be, in some cases, flagged and, where appropriate, excluded from calculations in determining whether or not an area has attained the standard" (EPA Exceptional Event Tutorial).

[16] There are 1,000 monitors that are active at least 1 year before and after (including) 2006. However, socio-economic data are missing for independent cities and one county in Virginia (Salem City, Lynchburg City, Bristol City, and Fairfax county), so 6 monitors located in these areas cannot be used for the regression analysis.

[17] One can also define "expected compliant monitor" as monitors that never violated the national standard between 2006 and 2011. However, this definition decreases the sample size significantly, with only 218 "expected compliant monitors". This smaller sample gives similar but weaker results for the monitor level analysis, as shown in Appendix Figure 11c and Appendix Table 5.

Figure 3: Expected Violating Monitors and Expected Compliant Monitors



Note: Shaded counties are $PM_{2.5}$ non-attainment counties between 2006 and 2011.

level, including income-per-capita, population, and GDP (real GDP in chained 2012 dollars). We also obtain county geographical data from the U.S. Census Bureau. The socio-economic data covers 3,080 counties in the contiguous U.S. (lower 48 states and Washington D.C.).

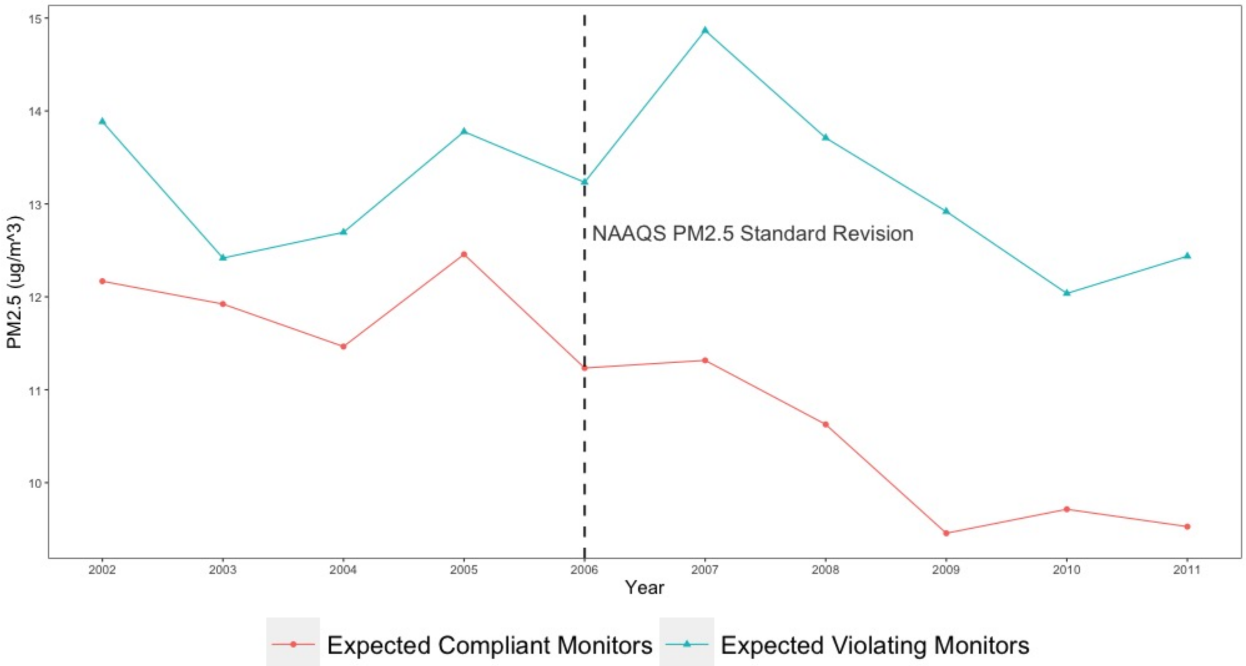
Table 1 reports the summary statistics for the monitor level sample. Compared with expected compliant monitors, expected violating monitors appear to have higher $PM_{2.5}$ readings and are located in areas with higher population density but lower income and GDP per capita.

3.2 Plant-by-Year Data

The raw TRI data is an unbalanced panel, consisting of 34,304 unique plants between 2002 and 2011. TRI does not report PM emissions, so we use the pollutant classifications from Greenstone (2003) to define plant level PM emissions as the total onsite air emissions of PM related chemicals.[18] We

[18]This method does not distinguish between $PM_{2.5}$ and PM_{10} emissions. However, this is unlikely to affect our analysis because the PM_{10} standard was unchanged between 2002 and 2011. Therefore, any change in total PM emissions due to the 2006 revision can be explained as the change in $PM_{2.5}$ emissions.

Figure 4: Unconditional Average Annual $PM_{2.5}$ Monitor Readings, "Expected Violating Monitors" versus "Expected Compliant Monitors"



exclude plants with misspecified geographical location and/or missing socio-economic information.[19] The final dataset covers 33,848 plants with 227,229 observations.

We divide all plants in our sample into three groups ("plants near expected violating monitors", "plants near expected compliant monitors", and "control plants") based on an arbitrarily chosen distance threshold of $d_0 = 5km$ between each plant and its nearest monitor by type. In particular, we define 793 plants as "plants near expected violating monitors" since they are within $5km$ of at least one "expected violating monitor"; 5,681 plants as "plants near expected compliant monitors" since they are within $5km$ of "expected compliant monitors" but more than $5km$ away from any of "expected violating monitor"; 27,374 plants as "control plants" since they are more than $5km$ away from all "expected violating monitors" and "expected compliant monitors". We assume that the $5km$ distance threshold is sufficiently large so that PM emissions from control plants did not affect the readings at any of the monitors in our sample and are thus not subject to local

[19]There are 126 plants with missing geographical information, and 320 plants located in counties with missing socio-economic data.

Table 1: Summary Statistics I: Monitor Level Sample (2002-2011)

Variable	All Monitors	Expected Violating Monitors	Expected Compliant Monitors
$PM_{2.5}$ Concentration ($\mu g/m^3$)	11.21	13.19	11.02
	(3.15)	(4.30)	(2.95)
Population Density (per KM^2)	445.69	705.06	421.28
	(1,378.57)	(2,254.36)	(1,273.59)
Income per Capita (dollars)	35,962.56	32,715.14	36,268.20
	(10,860.27)	(10,193.30)	(10,871.83)
GDP per Capita (dollars)	51,242.50	46,937.93	51,647.64
	(26,919.10)	(28,122.63)	(26,769.60)
Number of Monitors	994	128	866
Number of Observations	7,347	632	6,715

This table reports the mean statistics (s.d. in parentheses).

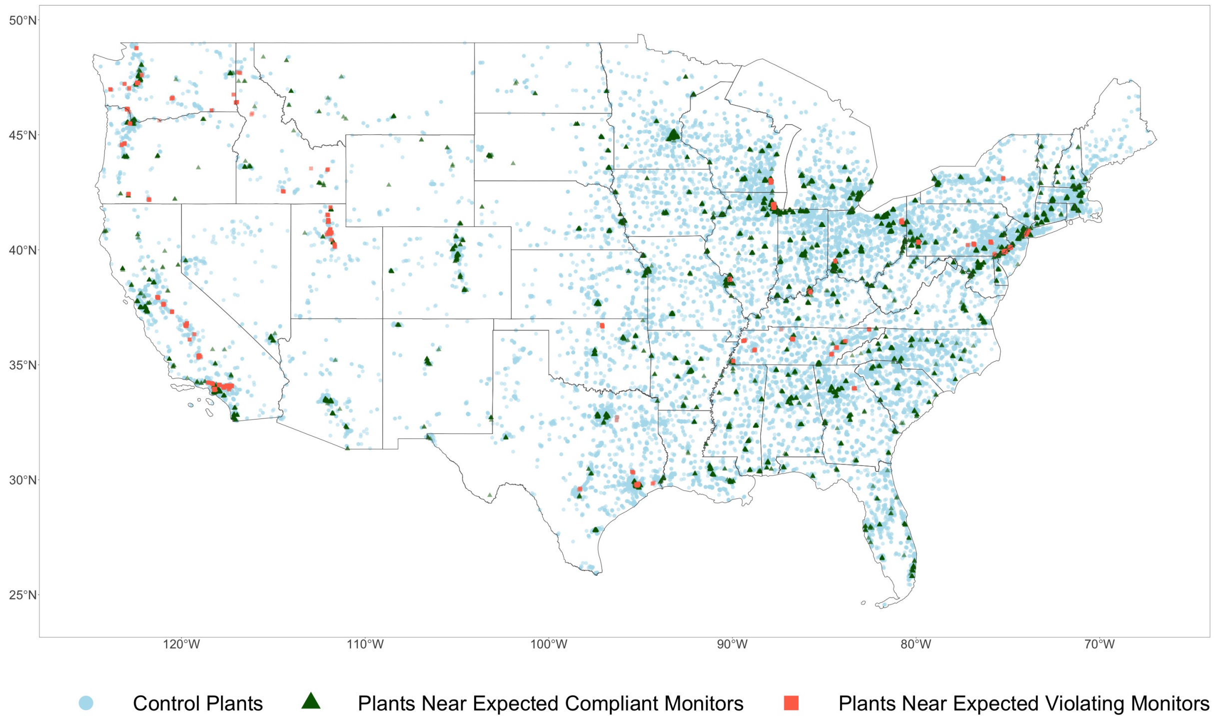
regulators' strategic behavior.[20] In the empirical analysis, we compare PM emissions from "plants near expected violating monitors" and "plants near expected compliant monitors", with "control plants", respectively. Figure 5 plots the location of all three groups of plants. The map shows that while TRI plants are overwhelmingly located in the eastern U.S., the geographic distribution of the three groups of plants has no apparent pattern. Figure 6 plots the average annual trend in unconditional PM emissions for all three groups of plants. Except for the fact that PM emissions from control plants are generally much higher, there are no clear trends in emissions across the three groups.[21]

In addition to the socio-economic characteristics included in the monitor level sample, we also control for county non-attainment status (obtained from the EPA Greenbook), plant characteris-

[20] There are 95 plants within $5km$ of both "expected violating monitors" and "expected compliant monitors", and their nearby "expected violating monitors" are not always active throughout our study period. We define them as "plants near expected compliant monitors". "Control plants" can be close to temporary monitors, which are only active either before or after the revision. We test the sensitivity of our results by excluding "control plants" near temporary monitors from our sample. See details in section 5.2.

[21] Figure 6 seems counter-intuitive since monitors are usually located in the areas with more emissions. However, such higher emissions are driven by a greater density of plants. We expect monitors are more likely to be located in the areas with a high density of emission sources, but when comparing average emissions per emission source, it is plausible that plants far away from monitors have higher emissions than the similar ones covered by monitors.

Figure 5: Location of Plants near Expected Violating Monitors, Plants near Expected Compliant Monitors, and Control Plants



tics including federal EPA inspections (obtained from the ECHO database) and the share of air emissions in total TRI onsite emissions across all media (calculated as $\frac{\textit{stack and fugitive air emissions}}{\textit{total onsite emissions}}$).[22]

Table 2 reports the summary statistics for the plant level sample. Among all three groups of plants, "control plants" have much higher PM emissions than others; plants near "expected violating monitors" are most likely to be located in non-attainment areas and with highest population density; plants near " expected compliant monitors" are most likely to be inspected by the federal EPA, and are located in areas with the highest income and GDP per capita.

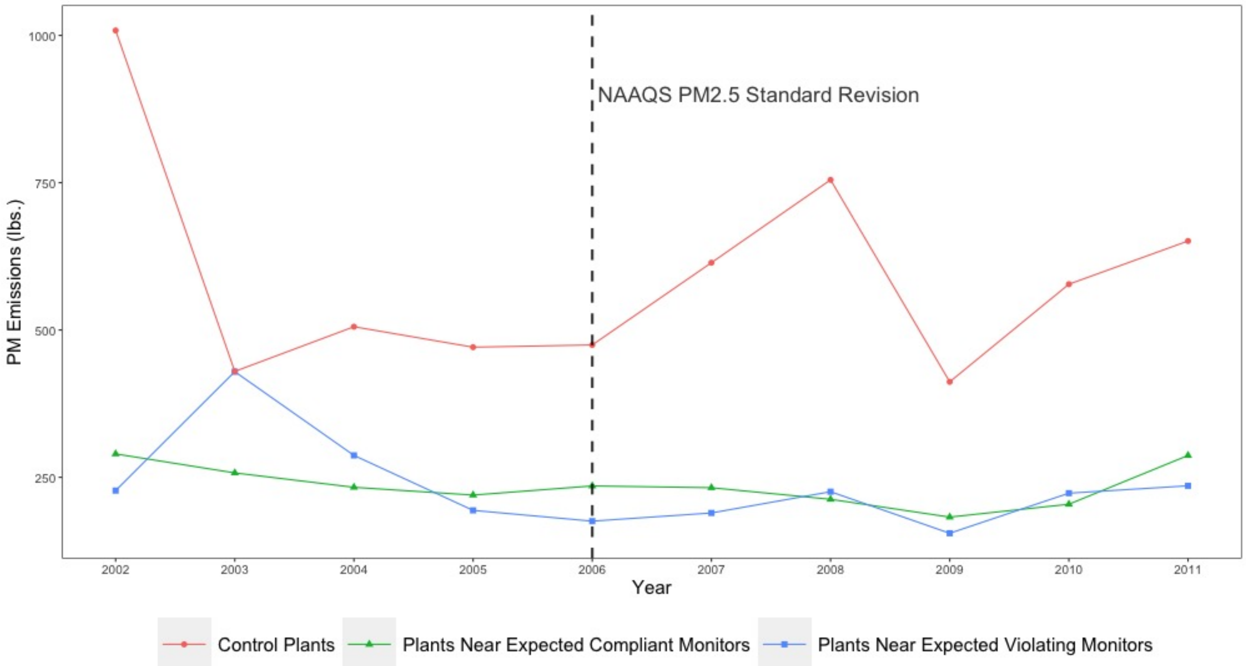
[22]County non-attainment status and EPA inspections capture the plant level variation in federal regulation pressure, which is expected to be negatively correlated with air emissions. The share of air emissions captures time-varying plant characteristics, which is expected to be positively correlated to air emissions.

Table 2: Summary Statistics II: Plant Level Sample (2002-2011)

Variable	All Plants	Plants near Expected Violating Monitors	Plants near Expected Compliant Monitors	Control Plants
PM Emissions (lbs.)	520.93	236.80	236.47	591.83
	(39,710.59)	(2,171.08)	(2,504.92)	(44,367.64)
County Non-attainment Status (dummy)	0.19	0.40	0.28	0.16
	(0.39)	(0.49)	(0.45)	(0.37)
EPA Inspections (annual counts)	0.05	0.03	0.07	0.04
	(0.51)	(0.27)	(0.70)	(0.47)
Air Emission Ratio	0.64	0.67	0.68	0.63
	(0.47)	(0.45)	(0.45)	(0.47)
Population Density (per KM^2)	295.08	604.98	531.42	233.93
	(578.27)	(1,346.31)	(929.64)	(393.28)
Income per Capita (dollars)	35,131.63	34,449.17	37,411.10	34,653.30
	(9,087.58)	(6,996.47)	(9,276.55)	(9,025.82)
GDP per Capita (dollars)	47,985.52	48,820.85	54,906.85	46,444.88
	(24,019.14)	(19,942.07)	(19,472.48)	(24,754.24)
Number of Plants	33,848	793	5,681	27,374
Number of Observations	227,229	5,520	39,821	181,888

This table reports the mean statistics (s.d. in parenthesis).

Figure 6: Annual Average Emissions of "plants near expected violating monitors", "plants near expected compliant monitors", and "control plants"



4 Empirical Analysis

In practice, our proposition translates into the following pair of empirically testable hypotheses: 1. a lowering of the national $PM_{2.5}$ standard leads to an increase in the gap of $PM_{2.5}$ readings between "expected violating monitors" and "expected compliant monitors"; 2. compared with control plants, a lowering of the national $PM_{2.5}$ standard leads to a decrease in $PM_{2.5}$ emissions of plants near "expected compliant monitors" but an increase in $PM_{2.5}$ emissions of plants near "expected violating monitors".[23] To test these two hypothesises, we use event studies and a difference-in-differences (DID) analysis at both the monitor and the plant level, respectively.

[23]The proposition implies that a more stringent revision of the national $PM_{2.5}$ standard leads to an increase in $PM_{2.5}$ readings at "expected violating monitors" and a decrease in $PM_{2.5}$ readings at "expected compliant monitors". However, since we do not have a good control group at the monitor level, we are not able to test this hypothesis. Instead, with such heterogeneous change in $PM_{2.5}$ readings and the fact that $PM_{2.5}$ readings are higher at "expected violating monitors" than "expected compliant monitors" (see Figure 4), the proposition also implies the first testable hypothesis.

4.1 Monitor Level Analysis

To compare $PM_{2.5}$ readings between "expected violating monitors" and "expected compliant monitors", we use an event study model to estimate annual gaps in $PM_{2.5}$ readings between the two groups of monitors, and compare the gaps before and after the revision. Consider the following event study regression:

$$y_{it} = \sum_{w=-3}^{-1} \alpha_w \times z_i \times 1[\tau_t = w] + \sum_{w=1}^{6} \alpha_w \times z_i \times 1[\tau_t = w] + \beta X_{it} + \gamma z_i + c_i + v_t + \epsilon_{it}, \quad (5)$$

where y_{it} is the annual $PM_{2.5}$ concentration in natural logs recorded at monitor i in year t.[24] τ_t is lag/lead between year t and year 2005 (one year before the revision), so that $\tau_t = t - 2005$. z_i is a dummy variable, with $z_i = 1$ if monitor i is an "expected violating monitor" and $z_i = 0$ otherwise. X_{it} is the vector of county-level socio-economic characteristics that are correlated with $PM_{2.5}$ pollution, described in Section 3. c_i is the county fixed effect, capturing unobserved county time-invariant characteristics. v_t is the year fixed effect. Similar to a "group fixed effect", the coefficient γ captures the average (intercept) difference between "expected compliant monitors" and "expected violating monitors".[25] α_w captures the remaining differences in yearly trends. Standard errors are clustered at the state level.

Figure 7 plots the estimated α_w and its 95% confidence interval. The results show that before the revision, there is no significant difference in $PM_{2.5}$ readings at "expected compliant monitors" versus "expected violating monitors". After the revision, relative to "expected compliant monitors", $PM_{2.5}$ readings at "expected violating monitors" are generally higher in every year.

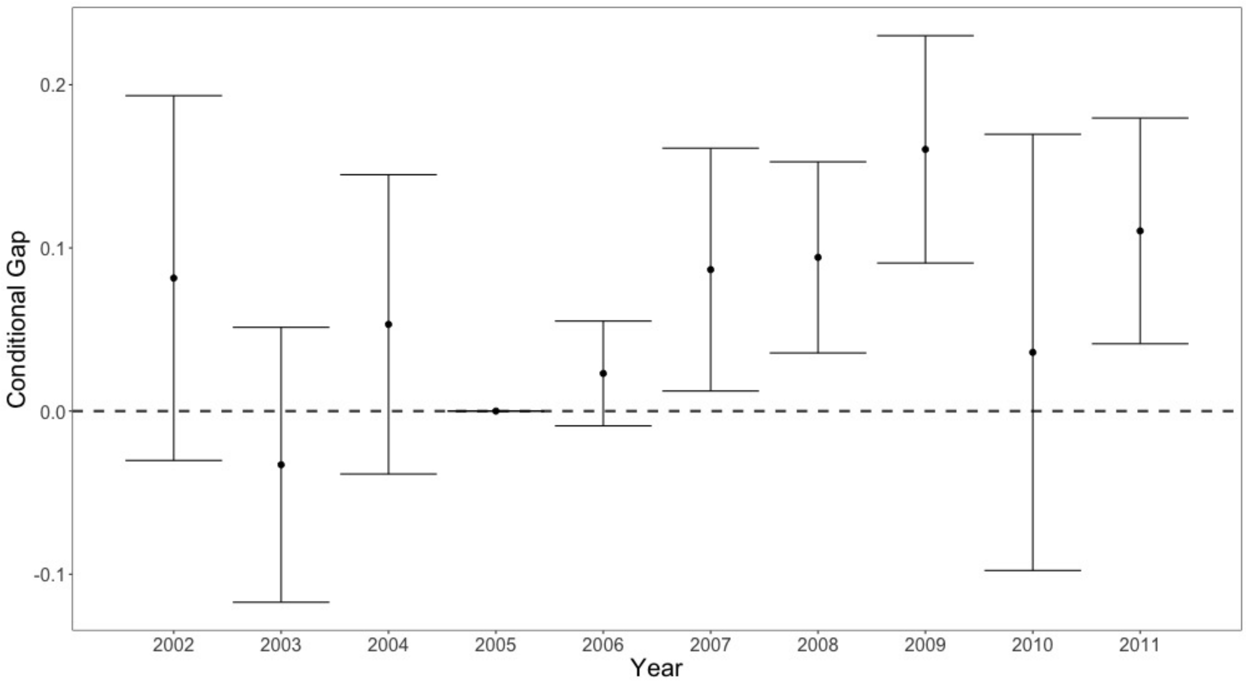
We also estimate a standard DID model to obtain the average effect of the NAAQS revision on $PM_{2.5}$ concentrations at "expected violating monitors" versus "expected compliant monitors":

$$y_{it} = \alpha_{DID} \times z_i \times I[t > 2005] + \beta X_{it} + \gamma z_i + c_i + v_t + \epsilon_{it}. \quad (6)$$

[24] Monitor $PM_{2.5}$ concentrations are all positive, so by taking natural logs we do not lose observations.

[25] We do not use monitor fixed effect in the regression because sometimes old monitors are retired and replaced by new monitors, but they cover the same area. The different $PM_{2.5}$ readings between old and new monitors represent the annual $PM_{2.5}$ time trend in the same area. However, if a monitor fixed effect is included, this difference will be captured by the monitor fixed effect and interpreted as an intercept difference rather than the time trend.

Figure 7: Event Study, Expected Violating Monitors vs. Expected Compliant Monitors



where α_{DID} is the DID estimator and γ captures the average pre-existing gap between the two groups of monitors. Table 3 reports the results. We find that regardless of model specification, estimated α_{DID} (reported in the Table as "Revision $\times$ Expected Violating") is always positive and significant, but omitting county fixed effect appears to bias the coefficient upwards. Also, we do not find any significant pre-existing gap between the two groups of monitors, as shown by the statistically insignificant coefficient on "expected violating monitors".

4.2 Plant level analysis

The plant level analysis covers all plants with emission information reported in the TRI database from 2002 to 2011. We conduct two comparisons: "plants near expected violating monitors" vs. "control plants", and "plants near expected compliant monitors" vs. "control plants". Consider the following event study regression at the plant level:

Table 3: Monitor Level Analysis: Difference-in-differences Results

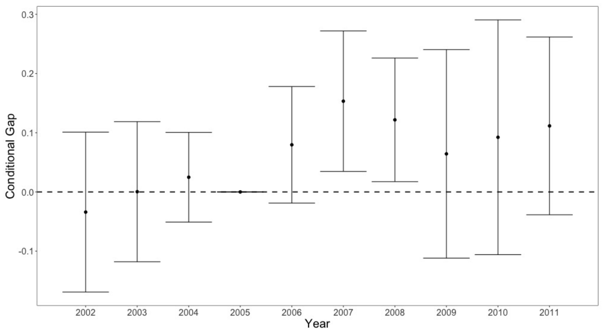
	Outcome Variable: log(annual $PM_{2.5}$ monitor readings, $\mu g/m^3$)			
Independent Variables	(1)	(2)	(3)	(4)
Revision × Expected Violating	0.190^{***}	0.080^{**}	0.181^{***}	0.078^{**}
	(0.055)	(0.037)	(0.051)	(0.037)
Expected Violating Monitors	0.077	0.144	0.067	0.146
	(0.117)	(0.113)	(0.117)	(0.113)
Population Density (100 people per KM^2)			0.004^{*}	−0.003
			(0.002)	(0.024)
Income per Capita ($1,000)			−0.002	−0.001
			(0.002)	(0.001)
GDP per Capita ($1,000)			0.0002	0.002^{**}
			(0.001)	(0.001)
County FE	N	Y	N	Y
Year FE	Y	Y	Y	Y
R^2	0.110	0.819	0.132	0.819
Adjusted R^2	0.109	0.801	0.131	0.802
Sample size	7,395	7,395	7,347	7,347

Note: Standard errors are clustered at the state level. There are fewer observations in column (3) and (4) because of missing social-economic variables for some counties. Significance level: *** p< .01, ** p<.05, * p<.1.

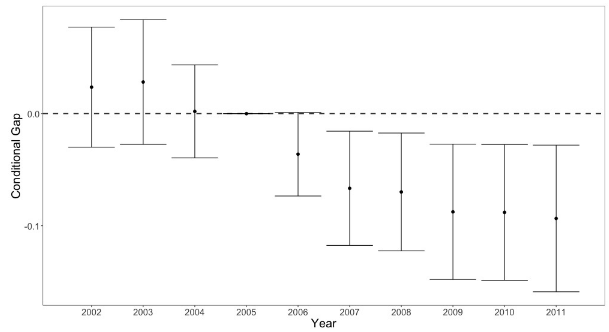
$$
\begin{aligned}
y_{it} = & \sum_{w=-4}^{-1} \alpha_w^1 \times g_i \times 1[\tau_t = w] + \sum_{w=1}^{5} \alpha_w^1 \times g_i \times 1[\tau_t = w] \\
& + \sum_{w=-4}^{-1} \alpha_w^2 \times h_i \times 1[\tau_t = w] + \sum_{w=1}^{5} \alpha_w^2 \times h_i \times 1[\tau_t = w] \\
& + \beta X_{it} + \gamma k_{it} + \mu_i + v_t + \epsilon_{it},
\end{aligned}
\tag{7}
$$

where $g_i = 1$ if plant i is a "plant near expected violating monitors" in year t and $g_i = 0$ otherwise; $h_i = 1$ if plant i is a "plant near expected compliant monitors" and $h_i = 0$ otherwise. X_{it} is a vector of local characteristics, k_{it} are plant characteristics (federal EPA inspections and the share of air emissions). μ_i and v_t are the plant and year fixed effects. α_w^1 captures the conditional gap in emissions between "plant near expected violating monitors" and "control plants", and α_w^2 captures the conditional gap in emissions between "plant near expected compliant monitors" and "control plants".

Figure 8: Plant Level Event Study



(a) "Plants near expected violating monitors" versus "control plants"



(b) "Plants near expected compliant monitors" versus "control plants"

Figures 8 plots the estimated α_w^1 and α_w^2. The results are strikingly consistent with our hypothesis. For "plants near expected violating monitors", PM emissions increased significantly after the 2006 revision, although the effect faded away after 2009.[26] For "plants near expected compliant monitors", PM emissions significantly decreased after 2006 revision, and the decline continued to persisted over time.

To estimate the average difference in plant emissions before and after the 2006 revision, we use the following regression model:

$$y_{it} = \alpha_{DID}^1 \times g_i \times I[t > 2005] + \alpha_{DID}^2 \times h_i \times I[t > 2005] + \beta X_{it} + \gamma g_{it} + \mu_i + v_t + \epsilon_{it}, \tag{8}$$

α_{DID}^1 and α_{DID}^2 are the DID estimators for the effect of the NAAQS revision on emissions of "plants near expected violating monitors" and "plants near expected compliant monitors", respectively. The results are reported in Table 4. As shown in the first two rows, the estimated α_{DID}^1 ("Near Expected Violating Monitors $\times$ Revision") is positive and significant whereas the estimated α_{DID}^2 ("Near Expected Compliant Monitors $\times$ Revision") is negative and significant. This is consistent with our hypothesis, suggesting that the revision significantly increased PM emissions of "plants near expected violating monitors" and significantly decreased PM emissions of "plants near expected

[26] We are unclear about why the effect fades away, but a plausible explanation is technology development that makes the air pollution abatement less expensive.

Table 4: Plant Level Analysis: Difference-in-differences Results

	Dependent variable:	
	log(PM + 0.1), PM emissions in lbs.	
	(1)	(2)
Near Expected Violating Monitors × Revision	0.106^{**}	0.106^{**}
	(0.053)	(0.051)
Near Expected Compliant Monitors × Revision	-0.086^{***}	-0.084^{***}
	(0.022)	(0.022)
Non-attainment County		-0.024
		(0.022)
Number of all EPA Inspection		-0.017
		(0.013)
Air Emission Ratio		0.908^{***}
		(0.067)
Population Density (100 people per KM^2)		0.055
		(0.038)
Income per Capita ($1,000)		-0.002
		(0.002)
GDP per Capita ($1,000)		0.002^{***}
		(0.001)
Plant FE	Y	Y
Year FE	Y	Y
Observations	229,436	227,229
R^2	0.891	0.895
Adjusted R^2	0.872	0.877

Note: For dependent variable, we add 0.1 to PM before taking natural logs to avoid losing observations with $PM = 0$. Standard errors are clustered at the state level. There are fewer observations in column (2) because of missing social-economic variables for some counties. Significance level: *** p< .01, ** p<.05, * p<.1.

compliant monitors".

5 Robustness Checks and Discussion

5.1 Robustness Checks for Monitor Level Analysis

For the monitor level analysis, we selected the monitor sample based on the criteria that the monitors must be active for at least one year before and after the revision. To test whether our results are sensitive to this sample selection criteria, we consider more relaxed/stricter sample selection criteria. Specifically, we re-estimate the monitor level regressions using the full sample of all monitors and with a selected sample of monitors that are active for at least three years before and after the revision.[27] In addition, we also use another selected sample of monitors that are ative for at least one year before and after the revision, and also either always comply with or always violate the national standard after the revision. We report the results with these three samples in Appendix Figures 11 and Tables 5. The results are very similar to our main results, except that the two selected samples yields smaller regression coefficients with lower statistical significance.

5.2 Robustness Checks for Plant Level Analysis

Plant Emissions near Temporarily Active Monitors

In the previous plant level analysis, we exclude temporarily active monitors from our sample. We acknowledge that plant emissions are likely to be affected by locally active monitors (including temporarily active monitors), given that local regulators may also strategically influence the location choices of active monitors (Grainger et al., 2020). To test whether our omission of temporarily active monitors from the sample affects our results, we re-estimate the plant-level regression by: 1. adding a dummy independent variable controlling for whether plants are near active monitors or not for each year (variable "near active monitor"); 2. Drop "control plants" near temporarily active monitors. Both results are reported in Appendix Figures 12 and the first two columns of Appendix Table 6. The results are very similar to our baseline results shown in Figures 8 and Table

[27]We use the same method described in Section 3.1 to define "expected compliant monitors" and "expected violating monitors".

4, and the coefficient on “near active monitor” is insignificant. This suggests that whether plant emissions are covered by temporarily active monitors or not is not correlated with the regulator's strategic behavior in allocating regulation resources and does not bias our results.

Plant Emissions Log Transformation

To avoid losing observations with zero emissions, we add 0.1 when taking logs of plant emissions. To test the sensitivity of our results regarding log transformation, we add 1 when taking logs and re-estimate the plant level regression. The results are presented in Appendix Figure 13 and column (3) of Appendix Table 6, which are very similar to our baseline results except relatively smaller coefficient magnitude and slightly lower significance. This is expected since by adding 1 make the data is more smoothed and flatter than adding 0.1 before taking logs.

Alternative Distance Threshold

To test whether our results are sensitive to the choice of distance threshold $d_0 = 5km$, we re-estimate the plant level regressions by setting $d_0 = 4km$ and $d_0 = 6km$. The results are reported in Appendix Figures 14 and columns (4) and (5) in Appendix Table 6. These results are again very similar to our baseline results for the plant level analysis.

6 Conclusion

The U.S. EPA, like other regulatory authorities across the world, has established national standards for regulating domestic pollution. Over time, and as the science evolves, these standards have been made more stringent with the expectation that domestic environmental quality will improve. Yet, there are areas in the U.S. where local air quality consistently exceeds the NAAQS despite persistent and increasing penalties for being in non-attainment. In this paper, we model the local regulator's strategic behavior and assess the efficacy of a more stringent national standard in reducing local pollution, given that local jurisdictions control regulation resources. Our theory suggests that for highly polluted areas, compliance with the national standard could be too expensive so that local regulators intentionally violate the standard; and a more stringent standard underscores the perverse incentive and results in worse air quality locally.

Using annual data for EPA monitors and TRI plant emissions, we assess the impacts of the 2006 revision of the 24-hour NAAQS for $PM_{2.5}$. Our empirical results are consistent with our theory: after the revision, we find a significant increase in both $PM_{2.5}$ monitor readings and industrial particulate matter emissions in the areas covered by “expected violating monitors”, where local regulators intentionally violate the national standard.

Our analysis highlights an unintended consequence of nationally uniform regulation policies due to local regulators' strategic behavior in a multi-level governance scenario. A better approach might be to set area-specific regulation standards or violation penalties and to make the standard more achievable, so that it can properly motivate local regulators to comply with.

A Online Appendix: Mathematical Proofs

A.1 Indirect Regulation Cost Function

Figure 9: Definition of Indirect Plant-specific Regulation Cost Function

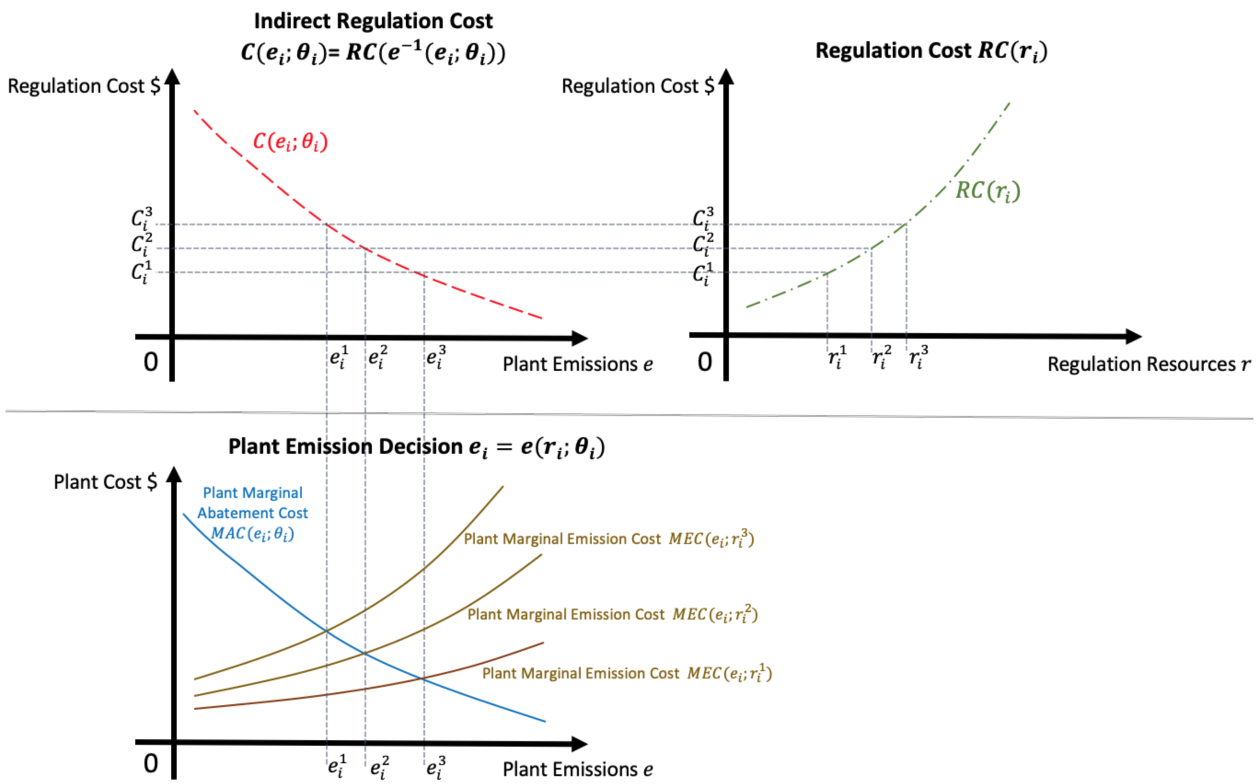


Figure 9 shows how we define the indirect regulation cost function. In the upper right panel, $RC(r_i)$ is the regulation cost, which is a function of regulation resources r_i allocated to plant i (for example, the frequency of environmental inspections). The regulation cost increases in the allocated regulation resources, so $RC'(r_i) = \frac{\partial RC(r_i)}{\partial r_i} > 0$. We assume that the cost of additional regulation resources increases (or is at least constant) as more regulation resources have been allocated, so $RC''(r_i) = \frac{\partial^2 RC(r_i)}{\partial r_i^2} \geq 0$.

The lower panel of Figure 9 describes plant decisions on emissions e_i. The plant minimizes its cost of emissions by balancing its own marginal abatement cost and marginal emission cost. Let $MAC(e_i;\theta_i)$ be the plant marginal abatement cost, depending on plant characteristics θ (such as size, industry, technologies, etc.). We assume that the plant marginal abatement cost increases as more emissions are abated (lower emissions e_i), so $MAC'(e_i;\theta_i) = \frac{\partial MAC(e_i;\theta_i)}{\partial e_i} < 0$. Let $MEC(e_i;r_i)$ be the plant marginal emission cost, generated by the allocated regulation resources r_i (for example, violation penalties when violations are found during environmental inspections). Since it is more likely for local inspections to find violations at plants with higher emissions, $MEC'(e_i;r_i) = \frac{\partial MEC(e_i;r_i)}{\partial e_i} > 0$. Also, given emissions e_i, more allocated regulation resources increase regulation pressure on the plant and thus raise the plant marginal emission cost (for example, more inspections increase the violation probability and expected penalties), so $\frac{\partial MEC(e_i;r_i)}{\partial r_i} > 0$. Given r_i and θ_i, plant optimal emissions $e_i(r_i;\theta_i)$ is the solution of plant cost minimization problem, where $MAC(e_i;\theta_i) = MEC(e_i;r_i)$.

Finally, as shown in the upper left panel of Figure 9, we combine $RC(r_i)$ and $e(r_i,\theta_i)$ to construct the indirect regulation cost function $C(e_i;\theta_i) = RC(e^{-1}(e_i;\theta_i))$, which represents the regulation cost C_i that is needed to allocate r_i regulation resources, which in turn generates enough regulation pressure to make the plant choose its optimal emission level at e_i.

To derive the slope and the curvature of $C(e_i;\theta_i)$, we use the inverse function of plant emissions $r_i = e^{-1}(e_i;\theta_i)$ to rewrite the plant cost minimization condition as

$$MAC(e_i;\theta_i) = MEC(e_i;e^{-1}(e_i;\theta_i)). \tag{9}$$

Taking the derivative of Equation 9 with respect to e_i gives

$$MAC'(e_i;\theta_i) = MEC'(e_i;e^{-1}(e_i;\theta_i)) + \frac{\partial MEC(e_i;r_i)}{\partial r_i}\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i}. \tag{10}$$

Since $MAC'(e_i;\theta_i) < 0$, $MEC'(e_i;e^{-1}(e_i;\theta_i)) > 0$, and $\frac{\partial MEC(e_i;r_i)}{\partial r_i} > 0$, we must have $\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i} < 0$. We do not make any assumptions regarding the curvature of the plant marginal emission cost and plant marginal abatement cost function, but we assume that with lower plant emissions e_i, additional regulation resources r_i are needed to further decrease e_i marginally, so $\frac{\partial^2 e(r_i;\theta_i)}{\partial r_i^2} > 0$, which also implies $\frac{\partial^2 e^{-1}(e_i;\theta_i)}{\partial e_i^2} > 0$.[28]

Therefore, with the conditions that $RC'() > 0$, $RC''(e^{-1}(e_i;\theta_i)) \geq 0$, $\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i} < 0$ and $\frac{\partial^2 e^{-1}(r_i;\theta_i)}{\partial e_i^2} > 0$, the indirect regulation cost function has the following properties:

$$\begin{aligned}
\frac{\partial C(e_i;\theta_i)}{\partial e_i} &= RC'(e^{-1}(e_i;\theta_i))\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i} < 0, \\
\frac{\partial^2 C(e_i;\theta_i)}{\partial e_i^2} &= RC''(e^{-1}(e_i;\theta_i))\Big(\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i}\Big)^2 + RC'(e^{-1}(e_i;\theta_i))\frac{\partial^2 e^{-1}(e_i;\theta_i)}{\partial^2 e_i} > 0,
\end{aligned}$$

A.2 Local Regulator's Optimal Solution

To find local minima and to rule out the saddle point for the local regulator's cost minimization problem, we consider second order condition. The local minimum is the solution to the first order condition with a positive definite Hessian matrix. Suppose there are n plants located in the area covered by monitor j, then $I_j = \{i_1, i_2, ..., i_n\}$. The Hessian matrix is:

$$H_j = \begin{bmatrix} h_{e_{i_1}e_{i_1}} & h_{e_{i_1}e_{i_2}} & \cdots & h_{e_{i_1}e_{i_n}} \\ h_{e_{i_1}e_{i_2}} & h_{e_{i_2}e_{i_2}} & \cdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ h_{e_{i_1}e_{i_n}} & h_{e_{i_2}e_{i_n}} & \cdots & h_{e_{i_n}e_{i_n}} \end{bmatrix},$$

where each element has the following expression:

for each particular plant ι diagonal element $h_{e_\iota e_\iota}$,

$$h_{e_\iota e_\iota} = C''(e_\iota;\theta_\iota) + G''\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)f^2(d_{\iota j}) - \psi'\Big(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i\Big)f^2(d_{\iota_1 j})K,$$

for each particular pair of plants ι_1 and ι_2 ($\iota_1 \neq \iota_2$), the off-diagonal element $h_{e_{\iota_1}e_{\iota_2}}$,

$$h_{e_{\iota_1}e_{\iota_2}} = G''\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)f(d_{\iota_1 j})f(d_{\iota_2 j}) - \psi'\Big(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i\Big)f(d_{\iota_1 j})f(d_{\iota_2 j})K,$$

[28] For inverse function $e(e^{-1}(e_i;\theta_i)) = e_i$, taking derivative on both side gives $\frac{\partial e(e^{-1}(e_i;\theta_i))}{\partial r_i}\frac{\partial e^{-1}(r_i;\theta_i)}{\partial e_i} = 1$. Given that $\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i} < 0$, we have $\frac{\partial e(e^{-1}(e_i;\theta_i))}{\partial r_i} < 0$. Taking second order derivative on both sides gives $\frac{\partial^2 e(e^{-1}(e_i;\theta_i))}{\partial r_i^2}\Big(\frac{\partial e^{-1}(r_i;\theta_i)}{\partial e_i}\Big)^2 + \frac{\partial e(e^{-1}(e_i;\theta_i))}{\partial r_i}\frac{\partial^2 e^{-1}(r_i;\theta_i)}{\partial e_i^2} = 0$. Given that $\frac{\partial e^{-1}(e_i;\theta_i)}{\partial e_i} < 0$, $\frac{\partial e(e^{-1}(e_i;\theta_i))}{\partial r_i} < 0$, and $\frac{\partial^2 e(r_i;\theta_i)}{\partial r_i^2} > 0$, we have $\frac{\partial^2 e^{-1}(r_i;\theta_i)}{\partial e_i^2} > 0$.

where $C''(\cdot)$ and $G''(\cdot)$ are second order derivatives. For a local minimum, the Hessian matrix must be positive definite, which means all diagonal elements must be positive. Therefore, we have the following property for ιth diagonal elements $h_{e_\iota e_\iota}$ for the global minimum:

$$-C''(e_\iota;\theta_\iota) + G''\Big(\beta X_j - \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big) f^2(d_{\iota j}) < -\psi'\Big(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i\Big) f^2(d_{\iota j})K, \quad (11)$$

where the left-hand side is the slope of marginal benefit curve and the right-hand side is the slope of marginal cost curve. This condition implies that the slope of marginal benefit curve must be smaller than the slope of marginal cost curve to reach a local minimum point. In the cases described in both Figure 1 and Figures 10, point a and c satisfy the second order condition, so they are local minimums. Point b is the local maximum and does not satisfy the second order condition.

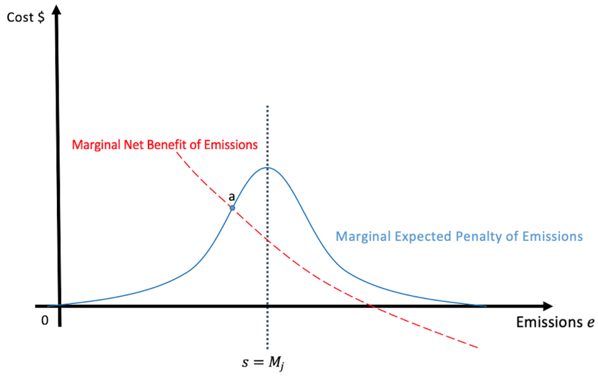
In the case described by Figure 1, monitor j can either be an "expected compliant monitor" or an "expected violating monitor", depending on whether the point a or c is the global minimum solution. Let e_i^h be the optimal regulated emissions of plant $i \in I_j$ with $M_j \geq s$, and e_i^l be the optimal regulated emissions of plant $i \in I_j$ with $M_j < s$.[29] The local regulator would choose e_i^l over e_i^h and expect that the monitor will be compliant with the national standard if the following condition is satisfied

$$\begin{aligned}&\sum_{i\in I_j} C(e_i^h;\theta_i) + G\Big(\beta X_j - \sum_{i\in I_j} f(d_{ij})e_i^h;\sigma_j\Big) + \Big(1 - Pr(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i^h)\Big)K \\ &\geq \sum_{i\in I_j} C(e_i^l;\theta_i) + G\Big(\beta X_j - \sum_{i\in I_j} f(d_{ij})e_i^l;\sigma_j\Big) + \Big(1 - Pr(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i^l)\Big)K.\end{aligned} \quad (12)$$

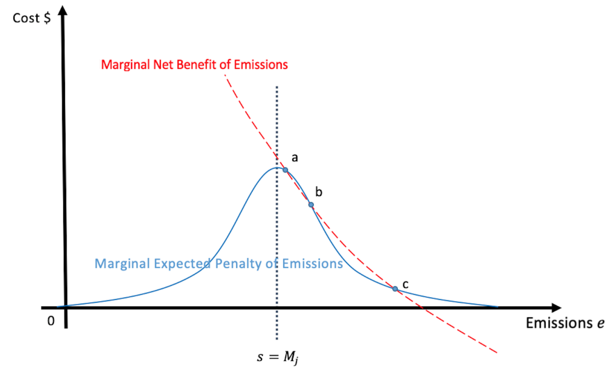
Otherwise, the local regulator would choose e_i^h over e_i^l and expect the monitor to violate the national standard.

[29] Note that in equation 11, the slope of marginal cost curves (right-hand side of the equation) for ιth plants in I_j only vary on the positive term $f(d_{\iota j})$, which implies that they share the same sign for all plants in I_j. Therefore, it is impossible for local regulator to mix the choices of e_i^l and e_i^h for plants $i \in I_j$ (plants covered by a unique monitor).

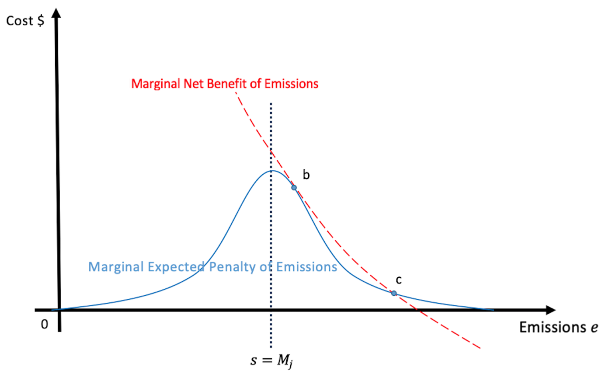
Figure 10: Additional cases for compliance/violating monitors



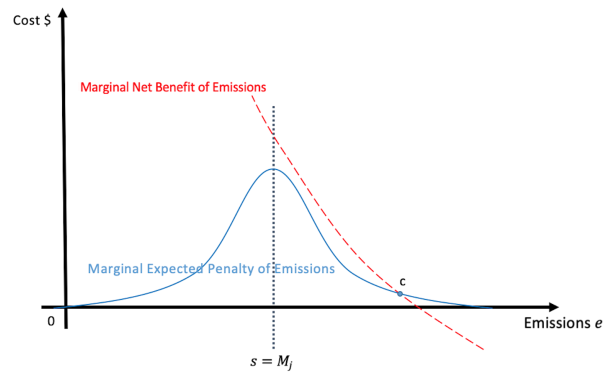
(a) Expected Compliance Monitor



(b) Expected Violating Monitor Case 1



(c) Expected Violating Monitor Case 2



(d) Expected Violating Monitor Case 3

A.3 Propositions and Proofs

Proposition: A more stringent national standard decreases emissions in areas covered by "expected compliant monitors" but increases emissions in areas covered by"expected violating monitors".

Proof:

From equation 4, we know that for every monitor j and each particular pair of plants ι_1 and ι_2 in I_j, with $f(d_{\iota_1 j}) > 0$ and $f(d_{\iota_2 j}) > 0$, we have

$$\begin{aligned}
\Big[-C'(e_{\iota_1};\theta_{\iota_1}) - G'\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)f(d_{\iota_1 j})\Big]\frac{1}{f(d_{\iota_1 j})} &= \psi\Big(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i\Big)K \\
\Big[-C'(e_{\iota_2};\theta_{\iota_2}) - G'\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)f(d_{\iota_2 j})\Big]\frac{1}{f(d_{\iota_2 j})} &= \psi\Big(s - \beta X_j - \sum_{i\in I_j} f(d_{ij})e_i\Big)K,
\end{aligned} \tag{13}$$

so that

$$\frac{C'(e_{\iota_1};\theta_{\iota_1}) + G'\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)f(d_{\iota_1 j})}{C'(e_{\iota_2};\theta_i) + G'\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)f(d_{\iota_2 j})} = \frac{f(d_{\iota_1 j})}{f(d_{\iota_2 j})}. \tag{14}$$

and we have

Lemma 1: For a local regulator, at optimal solutions, the ratio between marginal benefits of allowing emissions from different plants covered by a unique monitor, and with non-zero distance weights, equals the ratio of the distance weights.

Taking the derivative of equation 14 with respect to s gives

$$\begin{aligned}
&C''(e_{\iota_1};\theta_{\iota_1})f(d_{\iota_2 j})\frac{\partial e_{\iota_1}}{\partial s} + G''\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)\Big(f^2(d_{\iota_1 j})f(d_{\iota_2 j})\frac{\partial e_{\iota_1}}{\partial s} + f(d_{\iota_1 j})f^2(d_{\iota_2 j})\frac{\partial e_{\iota_2}}{\partial s})\Big) \\
=&C''(e_{\iota_2};\theta_{\iota_2})f(d_{\iota_1 j})\frac{\partial e_{\iota_2}}{\partial s} + G''\Big(\beta X_j + \sum_{i\in I_j} f(d_{ij})e_i;\sigma_j\Big)\Big(f(d_{\iota_1 j})f^2(d_{\iota_2 j})\frac{\partial e_{\iota_2}}{\partial s}) + f^2(d_{\iota_1 j})f(d_{\iota_2 j})\frac{\partial e_{\iota_1}}{\partial s}\Big),
\end{aligned}$$

$$C''(e_{\iota_1};\theta_{\iota_1})f(d_{\iota_2 j})\frac{\partial e_{\iota_1}}{\partial s} = C''(e_{\iota_2};\theta_{\iota_2})f(d_{\iota_1 j})\frac{\partial e_{\iota_2}}{\partial s}. \tag{15}$$

Since $C''(\cdot)$ and $f(\cdot)$ are positive, $\frac{\partial e_i}{\partial s}$ have the same sign for all $i \in I_j$. Therefore, we conclude that

Lemma 2: For all plants located in areas covered by the same monitor, the local regulator indirectly changes their emissions in the same direction in response to the change of the national standard. Taking the derivative of equation 4 with respect to s gives

$$\begin{aligned}
&-C''(e_\iota;\theta_\iota)\frac{\partial e_\iota}{\partial s}-G''\Big(\beta X_j+\sum_{i\in I_j}f(d_{ij})e_i;\sigma_j\Big)f(d_{\iota j})\sum_{i\in I_j}\big[f(d_{ij})\frac{\partial e_i}{\partial s}\big]\\
&=\psi'\Big(s-\beta X_j-\sum_{i\in I_j}f(d_{ij})e_i\Big)\times\Big(1-\sum_{i\in I_j}\big[f(d_{ij})\frac{\partial e_i}{\partial s}\big]\Big)\times f(d_{\iota j})K.
\end{aligned}\tag{16}$$

Let $I_j=\{i_1,i_2,...,i_n\}$, then equation 16 can be rewritten in matrix form:

$$-A_j\times\begin{bmatrix}\frac{\partial e_{i_1}}{\partial s}\\ \frac{\partial e_{i_2}}{\partial s}\\ \vdots\\ \frac{\partial e_{i_n}}{\partial s}\end{bmatrix}=(H_j-A_j)\times\begin{bmatrix}\frac{\partial e_{i_1}}{\partial s}\\ \frac{\partial e_{i_2}}{\partial s}\\ \vdots\\ \frac{\partial e_{i_n}}{\partial s}\end{bmatrix}+U_j,\tag{17}$$

where

$$\underset{(I_j\times I_j)}{A_j}=\begin{bmatrix}C''(e_{i_1};\theta_{i_1}) & 0 & 0 & \cdots & 0\\ 0 & C''(e_{i_2};\theta_{i_2}) & 0 & \cdots & 0\\ \vdots & \vdots & \vdots & \ddots & \vdots\\ 0 & 0 & 0 & \cdots & C''(e_{i_n};\theta_{i_n})\end{bmatrix},$$

$$\underset{(I_j\times 1)}{U_j}=\begin{bmatrix}\psi'\Big(s-\beta X_j-\sum_{i\in I_j}f(d_{ij})e_i\Big)f(d_{i_1 j})K\\ \psi'\Big(s-\beta X_j-\sum_{i\in I_j}f(d_{ij})e_i\Big)f(d_{i_2 j})K\\ \vdots\\ \psi'\Big(s-\beta X_j-\sum_{i\in I_j}f(d_{ij})e_i\Big)f(d_{i_n j})K\end{bmatrix}.$$

Rearranging equation 17 gives

$$\begin{bmatrix}\frac{\partial e_{i_1}}{\partial s}\\ \frac{\partial e_{i_2}}{\partial s}\\ \vdots\\ \frac{\partial e_{i_n}}{\partial s}\end{bmatrix}^T\times H_j\times\begin{bmatrix}\frac{\partial e_{i_1}}{\partial s}\\ \frac{\partial e_{i_2}}{\partial s}\\ \vdots\\ \frac{\partial e_{i_n}}{\partial s}\end{bmatrix}=-\begin{bmatrix}\frac{\partial e_{i_1}}{\partial s}\\ \frac{\partial e_{i_2}}{\partial s}\\ \vdots\\ \frac{\partial e_{i_n}}{\partial s}\end{bmatrix}^T\times U_j.\tag{18}$$

The Hessian matrix for a local minimum is positive definite, so equation 18 implies

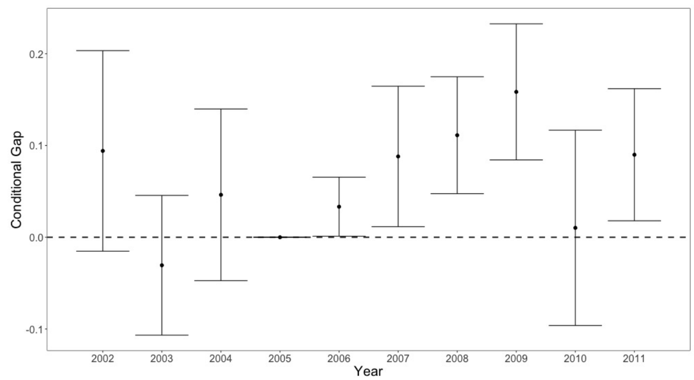
$$\begin{bmatrix} \frac{\partial e_{i_1}}{\partial s} \\ \frac{\partial e_{i_2}}{\partial s} \\ \vdots \\ \frac{\partial e_{i_n}}{\partial s} \end{bmatrix}^T \times U_j < 0. \tag{19}$$

All the elements of U_j share the same sign, which depends only on the sign of $\psi'(\cdot)$. Therefore, together with Lemma 2, we conclude that if monitor j is an "expected violating monitor" with its expected readings above the national standard, $\frac{\partial e_i}{\partial s} < 0$ for $i \in I_j$; if monitor j is an "expected compliant monitor" with its expected readings below or equal to the national standard, $\frac{\partial e_i}{\partial s} > 0$ for $i \in I_j$. This result also implies that for an "expected compliant monitor", a more stringent national standard motivates the local regulator to allocate more resources to regulating local pollution, which lowers local pollution and monitor readings; in contrast, for an "expected violating monitor", a more stringent national standard discourages the local regulator from investing in local pollution so that local pollution and monitor readings increase.

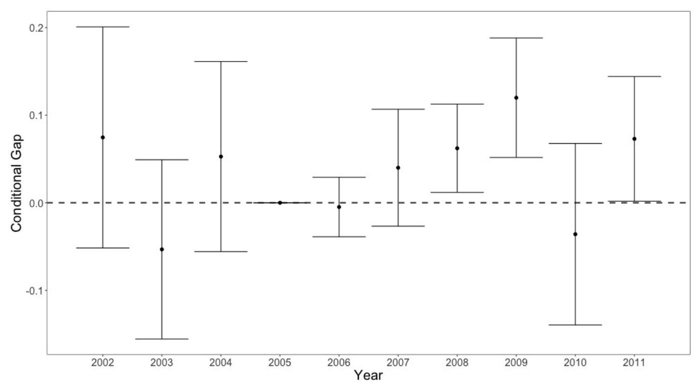
B Online Appendix: Additional Empirical Results

B.1 Monitor Level Robustness Checks

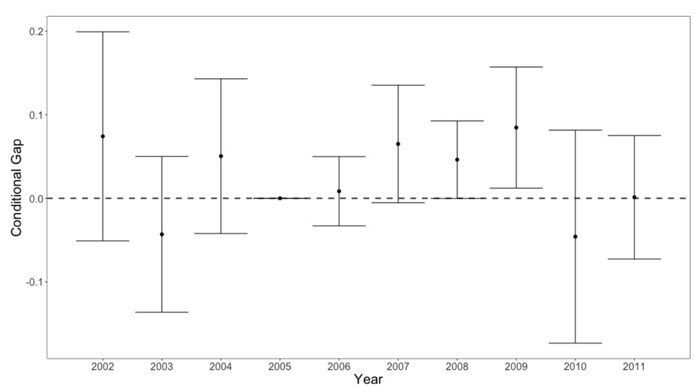
Figure 11: Monitor Level Robustness Check: Different Sample Selection Criteria



(a) No sample selection



(b) Monitors active for at least three years before and after the revision



(c) Monitors active for at least three years before and after the revision, “expected compliant monitors” are defined as monitors that never violated the national standard

Table 5: Monitor Level Robustness Checks: DID Results

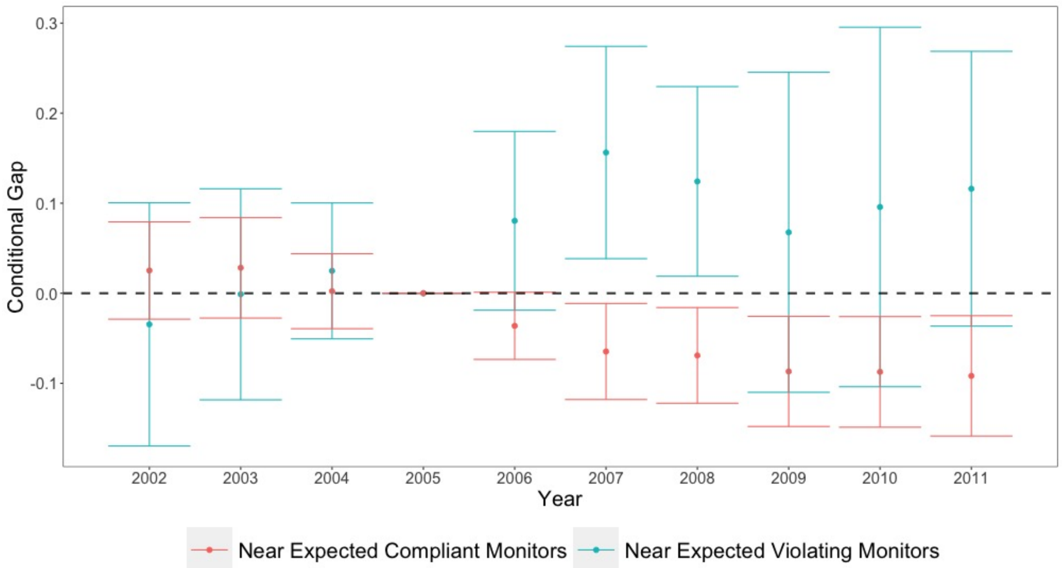
	Dependent variable:		
	log(annual $PM_{2.5}$ monitor, readings, ($\mu g/m^3$))		
	(1)	(2)	(3)
Revision × Expected Violating	0.067**	0.045	0.019
	(0.033)	(0.040)	(0.037)
Expected Violating Monitors	0.131	0.205	0.437*
	(0.104)	(0.140)	(0.231)
Population Density (100 people per KM^2)	−0.005	−0.007	0.050
	(0.023)	(0.022)	(0.080)
Income per Capita ($1,000)	−0.001	−0.000	−0.001
	(0.002)	(0.001)	(0.001)
GDP per Capita ($1,000)	0.002**	0.002**	0.004**
	(0.001)	(0.001)	(0.001)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	8,477	6,421	2,072
R^2	0.810	0.832	0.862
Adjusted R^2	0.791	0.816	0.841

Note: Standard errors are clustered at the state level. Regressions are the same as plant the level regression in the paper except: column (1) uses the full sample of all monitors; column (2) uses the sample of monitors that were active for at least 3 years before and after the revision; column (3) uses the sample of monitors that were active for at least 1 years before and after the revision, and were either always compliant with or always violate the national standard. Significance level: *** p< .01, ** p<.05, * p<.1.

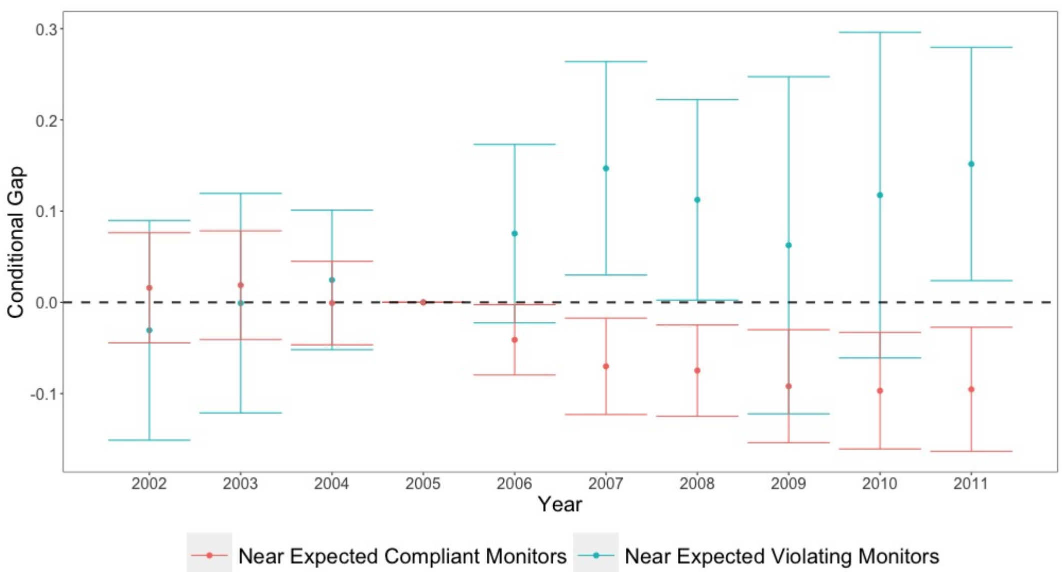
B.2 Plant Level Robustness Checks

Robustness Test: Plant Emissions near Temporarily Active Monitors

Figure 12: Plant Level Robustness Check: Temporarily Active Monitors, Event Study



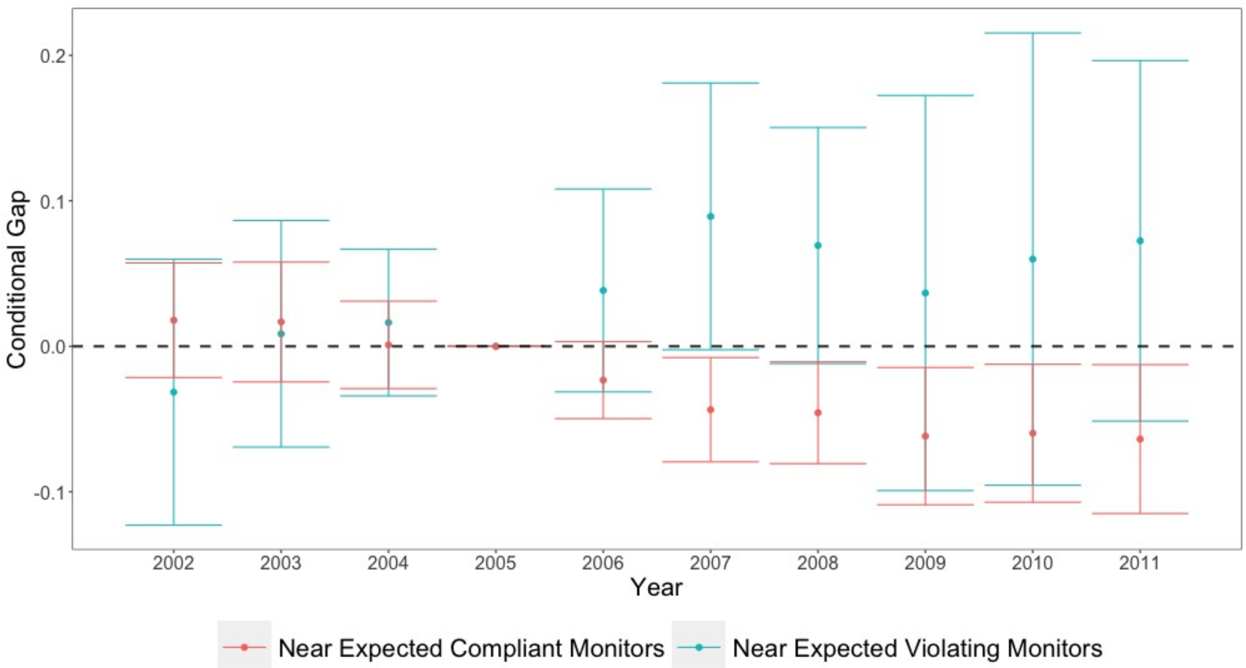
(a) Control "near active monitors"



(b) Exclude control plants near temporarily active monitors

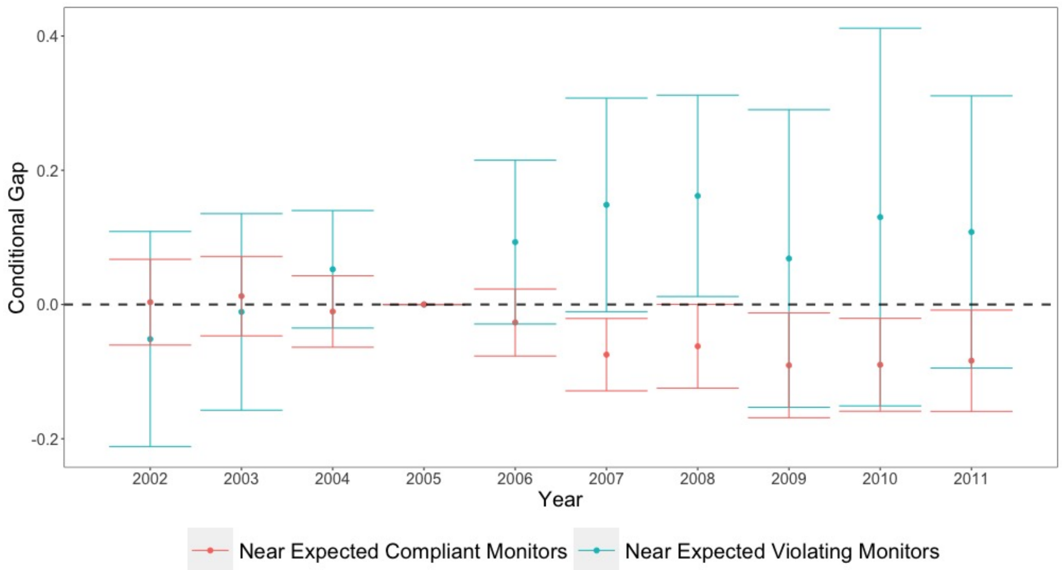
Robustness Test: log(Emissions+1)

Figure 13: Plant Level Robustness Check: log(Plant Emissions+1)



Alternative Distance Threshold

Figure 14: Plant Level Robustness Check: Alternative Distance Threshold, Event Study



(a) Distance Threshold $d_0 = 4km$

(b) Distance Threshold $d_0 = 6km$

DID Results of Plant Level Robustness Checks

Table 6: Plant Level Robustness Checks: DID Results

	Dependent variable: PM emissions in lbs.				
	log(PM + 0.1) *(Temp. Monitors)*		*log(PM + 1)* *(Log Trans.)*	*log(PM + 0.1)* *(Diff. d_0)*	
	(1)	(2)	(3)	(4)	(5)
Near Expected Violating Monitors × Revision	0.109**	0.110**	0.062	0.109	0.072*
	(0.051)	(0.049)	(0.040)	(0.079)	(0.038)
Near Expected Compliant Monitors × Revision	−0.083***	−0.083***	−0.056***	−0.071**	−0.081***
	(0.022)	(0.021)	(0.015)	(0.028)	(0.023)
Near Active Monitor	0.013				
	(0.015)				
Non-attainment County	−0.024	−0.020	−0.014	−0.026	−0.023
	(0.022)	(0.022)	(0.016)	(0.022)	(0.022)
EPA Inspection	−0.017	−0.017	−0.016	−0.017	−0.017
	(0.013)	(0.013)	(0.010)	(0.013)	(0.013)
Air Emission Ratio	0.908***	0.906***	0.553***	0.908***	0.908***
	(0.067)	(0.066)	(0.043)	(0.067)	(0.067)
Population Density (100 people per KM^2)	0.001	0.001	0.041	0.001	0.001
	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)
Income per Capita ($1,000)	−0.002	−0.002	−0.001	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GDP per Capita ($1,000)	0.002***	0.003***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Plant & Year FE	Y	Y	Y	Y	Y
Observations	227,229	221,363	227,229	227,229	227,229
R^2	0.895	0.896	0.892	0.895	0.895
Adjusted R^2	0.877	0.877	0.873	0.877	0.877

Note: Standard errors are clustered at the state level. Regressions are the same as the plant level regression in the paper except: column (1) reports results with full sample but controlling for "near active monitors", column (2) drops "control plants" near temporarily active monitors; column (3) uses $log(PM+1)$ instead of $log(PM+0.1)$ as the outcome variable; column (4) uses distance threshold $d_0 = 4km$, column (5) uses distance threshold $d_0 = 6km$. Significance level: *** p< .01, ** p<.05, * p<.1.

References

Auffhammer, M., A. M. Bento, and S. E. Lowe (2009). Measuring the effects of the clean air act amendments on ambient concentrations: The critical importance of a spatially disaggregated analysis. *Journal of Environmental Economics and Management 58*(1), 15–26.

Gibson, M. (2019). How states comply with federal regulations: Strategic ambient pollution monitoring. *The Review of Economics and Statistics 101*(5), 827–840.

Grainger, C., A. Schreiber, and W. Chang (2020). Do regulators strategically avoid pollution hotspots when siting monitors? evidence from remote sensing of air pollution. *Working paper*.

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of Political Economy 110*(6), 1175–1219.

Greenstone, M. (2003). Estimating regulation-induced substitution: The effect of the clean air act on water and ground pollutions. *AEA Papers and Proceedings 93*(1), 442–449.

Mu, Y., E. A. Rubin, and E. Zou (2021). What's missing in environmental (self-)monitoring: evidence from strategic shutdown of pollution monitors. *NBER Working Paper 28735*.

Rabassa, M. J. (2008). Ambient air pollution and the allocation of environmental enforcement effort. *Unpublished Manuscript*.

Zou, E. (2021). Unwatched pollution: The effect of intermittent monitoring on air quality. *American Economic Review 111*(7), 2101–26.