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Escalation of Scrutiny: The Gains from Dynamic Enforcement of Environmental Regulations†

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The US Environmental Protection Agency (EPA) uses a dynamic approach to enforcing air pollution regulations, with repeat offenders subject to high fines and designation as high priority violators (HPV). We estimate the value of dynamic enforcement by developing and estimating a dynamic model of a plant and regulator, where plants decide when to invest in pollution abatement technologies. We use a fixed grid approach to estimate random coefficient specifications. Investment, fines, and HPV designation are costly to most plants. Eliminating dynamic enforcement would raise pollution damages by 164 percent with constant fines or raise fines by 519 percent with constant pollution damages. (*JEL* Q52, Q53, Q58)

In the United States, the Clean Air Act and its amendments reduced damages from air pollution by $35.3 trillion from 1970 to 1990. However, since these regulations impact nearly every industrial facility in the United States, combined enforcement and compliance costs to governments and plants over this period were also large: $831 billion (EPA 1997, converted to US$(2007)). While the benefits appear to justify the costs, the sheer magnitude of these costs makes it critical to understand the efficiency of regulatory monitoring and enforcement mechanisms for pollution control.

To better understand how environmental regulations are enforced, first consider an example of a large oil refinery in Texas.[1] In 2011, after a period with only low-level violations, the plant was conducting work to improve productive efficiency when a valve that should have been left open was closed. This led to a pressure buildup in a

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[1] We obtained the information underlying this example from our analysis data, described in Section IIA, and documents from Texas (Texas Commission on Environmental Quality 2019).

pipeline, causing a leak and emissions of volatile organic compounds and benzene. Because these emissions came from an unauthorized source within the facility, the plant was placed in *high priority violator* (HPV) status, subjecting it to higher scrutiny and fines. In 2012, another low-level pollution release similar to the earlier ones occurred, but this time the fine imposed was doubled because the plant was in HPV status. Increased scrutiny and enhanced fines continued through a series of additional releases until the plant made two separate investments in pollution abatement and monitoring, after which it was removed from HPV status, returning to a baseline level of scrutiny in 2013.

This example illustrates one way that the US Environmental Protection Agency (EPA) uses *dynamic enforcement*—where regulatory actions are a function of the plant's history of past actions (Landsberger and Meilijson 1982, Shimshack 2014)—to enforce the Clean Air Act Amendments (CAAA). Specifically, the EPA designates repeat offenders as HPVs and targets them with elevated scrutiny and penalties. Regulators may choose dynamic enforcement because it avoids over-fining plants before they have a chance to fix violations, but uses the threat of high fines as an incentive for plants to make costly investments in pollution abatement. Dynamic enforcement may add value when the imposition of fines is costly to the regulator and also when the regulator cannot contract on a plant's compliance costs with its regulatory policies.

CAAA enforcement incorporates substantial state-dependent scrutiny, in part through HPV status designation. To illustrate this, Figure 1 shows mean unconditional CAAA inspection rates, violation rates, and fines separately for plants in compliance, regular (not-high-priority) violators, and HPVs. In each case, the level of scrutiny increases dramatically with regulatory status.[2]

This paper seeks to quantify the gains from dynamic enforcement of the CAAA. To do this, we first estimate the cost to industrial facilities of complying with the EPA's current dynamic approach. We then simulate the value of alternative enforcement regimes in affecting plants' emissions and compliance with the CAAA. Our modeling and estimation framework are specific to the CAAA, but we believe that similar approaches may yield important general insights, since dynamic enforcement is used across many settings. While the theoretical value of dynamic enforcement is well established, our contribution is to provide evidence on the degree to which this value holds empirically.

In order to measure the value of dynamic enforcement, one needs to account for its benefit in lowering pollution damages and weigh that against the compliance costs to plants and regulators. Measuring this value requires estimating a dynamic model of the costs to plants from investment in pollution abatement relative to the costs of regulatory scrutiny. In our model, the plant and regulator play a discrete-time dynamic game. The regulator makes decisions regarding inspections and fines. Inspections help the regulator obtain more precise information about CAAA compliance. Using its information—including from the inspection when one is performed—the regulator determines whether violations have occurred and decides whether to transition plants to regular or high priority violator status. Both

[2] The increasing pattern for fines in Figure 1 could be due to dynamic enforcement or to those plants violating environmental norms more frequently or severely. Our analysis allows for both of these explanations.

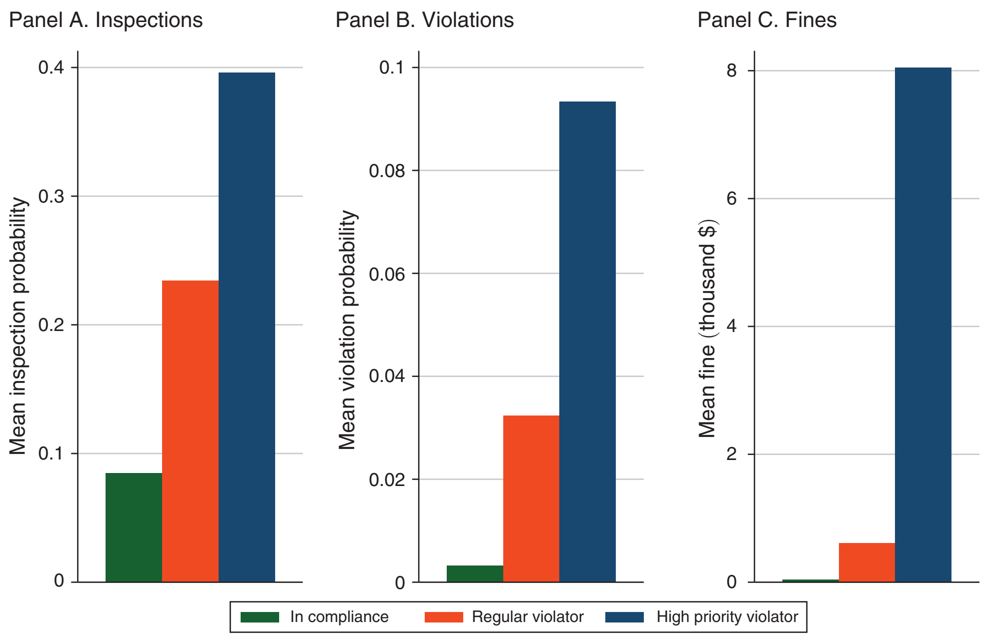

Figure 1. EPA Clean Air Act Amendment Enforcement by Regulatory Status

Note: Figure reports 2007–2013 unconditional mean quarterly levels of inspections, violations, and fines by CAAA regulatory status, based on authors' calculations from the estimation sample.

outstanding violations and elevated regulatory status can subject plants to higher inspection rates and higher fines. The regulator bears a cost from conducting inspections and imposing fines. To avoid making assumptions about the EPA's objective function, we do not estimate the regulator's utility function, but rather model the regulator's decisions using conditional choice probabilities (CCPs).

Plants decide whether and when to invest in pollution abatement technologies and potentially bear costs from both regulatory actions (e.g., shutting down a production line to allow for an inspection) and investment in pollution abatement. Therefore, a plant that is in regular or high priority violator status will consider investing in order to reduce its present discounted value of future regulatory costs. Recovering these costs is key to understanding how plants will respond to counterfactual regulatory policies, such as those that do not condition enforcement activities on plant state.

Our estimation makes use of extensive data with information on virtually all industrial facilities in high polluting industries covered by the CAAA. Our data report inspections, violations, fines, compliance status, and investment decisions for a seven-year-long panel with over 2.3 million plant/quarter observations. These data allow us to estimate plant costs with a nonparametric random coefficients model. We specify a fixed grid of potential cost parameters and estimate the population weights of each. We use a generalized method of moments (GMM) estimator that is computationally very tractable, with a quick and convex optimization problem. Using our estimated cost parameters, we evaluate the gains from dynamic enforcement by computing the pollution damages, assessed fines, and other outcomes when plants optimize under counterfactual regulatory policies.

Relation to Literature.—This paper relates to three distinct literatures. First, there is an empirical literature on the enforcement of environmental regulations that has largely focused on estimating the relationship between compliance and enforcement.[3] A number of papers also show that dynamic enforcement exists across a variety of contexts.[4] We add to this literature by estimating the value of dynamic enforcement of environmental regulations.

Second, we build on the structural environmental economics literature (e.g., Timmins 2002; Ryan 2012; Lim and Yurukoglu 2018; Muehlenbachs 2015; Fowlie, Reguant, and Ryan 2016; Duflo et al. 2018; Houde 2018; Kang and Silveira 2019). In particular, Duflo et al. (2018) and Kang and Silveira (2019) estimate regulator preferences in order to evaluate the value of regulator discretion. Duflo et al. (2018) consider a dynamic model of air pollution regulation in India (but do not investigate dynamic enforcement), while Kang and Silveira (2019) consider a static model of water pollution enforcement in California. Though our settings are different, these papers also highlight the value of heterogeneous enforcement.

Third, we use a nonparametric estimating framework for dynamic discrete choice models with random coefficients (Arcidiacono and Miller 2011; Fox et al. 2011; Gowrisankaran and Rysman 2012; Connault 2016; Fox, Kim, and Yang 2016; Nevo, Turner, and Williams 2016). In this dimension, our paper is most similar to Fox et al. (2011); Fox, Kim, and Yang (2016); and Nevo, Turner, and Williams (2016) in that it uses the same fixed grid GMM approach and similar computational techniques.

I. Dynamic Enforcement in Practice and Theory

A. *Dynamic Enforcement under the Clean Air Act Amendments*

Congress passed the Clean Air Act in 1963 in an effort to improve air quality. While the original act mostly provided funds for research into monitoring and limiting air pollution, a series of amendments starting in 1965 codified air pollution standards and federal enforcement of these standards. Following the National Environmental Policy Act of 1969 and the 1970 Clean Air Act Amendment, the EPA was created to enforce air pollution standards and other environmental legislation. The act was last amended in 1990 to expand the scope of regulated air pollutants and increase federal enforcement authority. The Clean Air Act combines with its amendments to form the current structure of air pollution regulation enforcement. We will refer to the CAAA in what follows.

[3] For instance, Magat and Viscusi (1990) examine whether inspections lower emissions at a plant, Nadeau (1997) uses variation across plant types and states to look at the effect of enforcement on the duration of noncompliance, Shimshack and Ward (2008) show that increased enforcement can lead even compliant plants to reduce emissions, leading to "over-compliance," where plants emit well below the compliance threshold, and Stafford (2002), Keohane, Mansur, Voynov (2009), and Blundell (2020) examine how variation in the intensity of dynamic enforcement relates to plants' compliance status.

[4] E.g., for the CAAA (Evans 2016) and the Clean Water Act (Earnhart 2004, Shimshack and Ward 2005) in the United States, petroleum storage in Canada (Eckert 2004), air pollution in Norway (Telle 2013), soil, water, and air pollution in Belgium (Blondiau, Billiet, and Rousseau 2015), and waste management in Japan (Shinkuma and Managi 2012). Dynamic enforcement is also widely used beyond environmental regulations, e.g., in worker health and safety regulation (Ko, Mendeloff, and Gray 2010) and tax auditing in China (Maitra et al. 2007).

The CAAA give the EPA the authority to regulate criteria air pollutants—ozone (O_3), particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_X), sulfur dioxide (SO_2), and lead (Pb)—as well as various hazardous air pollutants. The CAAA mostly mandate command-and-control regulations, which require that plants' pollution be at or below thresholds that could be achieved with the best technologies and practices.[5] To ensure that plants comply with these regulations, the EPA has developed an enforcement regime that includes a system of permitting, inspections, violations, fines, and other requirements (e.g., self-reporting paperwork). This enforcement structure aims to reduce pollution by ensuring that plants are complying with the CAAA emissions and technology standards and by encouraging plants that are out of compliance to return to compliance via plant investments in improved processes or technology.

While the CAAA and EPA dictate the structure of CAAA enforcement, much of the actual enforcement activity is carried out by regional- and state-level environmental protection agencies.[6] In particular, the EPA divides the country into ten geographic regions (EPA 2017). Significant portions of the EPA's operations are conducted through these regional offices. For instance, regional EPA offices conduct inspections and/or issue sanctions when a state's enforcement is below required levels, and assist states with major cases. Further, EPA guidance explicitly states that "regions and states can take varied approaches to improving state enforcement programs" (EPA 2013, p.5). Thus, EPA regions and states represent geographic areas across which the interpretation of federal policy and preferences for enforcement may vary.

Under the enforcement system used during our sample period, all plants—in compliance or otherwise—could expect to be inspected regularly. The frequency of these inspections depended not only on baseline differences across states and regions in enforcement budgets and priorities, but also on the size of the plant and whether the plant was located in a National Ambient Air Quality Standards (NAAQS) non-attainment area. Non-attainment areas were required to have plans to return to attainment, which could lead to increased levels of scrutiny for plants in these areas.

In the course of an inspection, or via a plant self-report, regulators may uncover a violation of the CAAA, and the plant will enter "violator" status. Being a violator subjects the plant to additional inspections, which could possibly uncover additional violations and potential fines. Plants can accumulate multiple violations within violator status and will only return to compliance once those violations have been resolved. The cost to the plant of being a violator therefore comes not only from the investment cost required to resolve outstanding violations, but also from an increased level of regulatory oversight.

In addition to conducting inspections and identifying violations, the EPA can issue fines to plants. Fines are calculated using two main components: the gravity

[5] The CAAA include some market-based regulations, such as the NO_X cap-and-trade program. However, these regulations incentivize reductions in NO_X emissions beyond the command-and-control requirements. Importantly, plants cannot simply purchase cap-and-trade permits to ensure CAAA compliance.

[6] While many of these state agencies are called something other than an "EPA" (e.g., the Florida Department of Environmental Protection), we will refer to them as state EPAs for brevity. State and regional EPAs are required to maintain a minimum level of enforcement, but can exceed this threshold (Shimshack 2014).

of the violation and the economic benefit that the plant received from the violation (EPA 1991). The gravity component of each violation is primarily determined from the actual or potential harm of the violation, which includes (i) the level of the violation, (ii) the toxicity of the pollutant, (iii) the sensitivity of the environment into which the pollutant is released, and (iv) the duration of the violation. Additionally, gravity is adjusted based on a number of other factors including whether there were reporting issues (e.g., permitting and self-reporting violations), the plant's history of noncompliance, and the plant's ability to pay.[7] Our modeling of regulator fines takes these features into account through the plant's history of violations and recent investments and a series of fixed effects that seek to capture a plant's economic benefit of noncompliance and gravity, based on the plant's industry and location. Finally, because of bankruptcy laws, political pressure, and explicit caps, the EPA is limited in the penalties it can assess. In particular, driving plants out of business for small infractions would undermine political support for the CAAA and EPA. Thus, there is an advantage to the EPA of obtaining compliance without issuing numerous large penalties.

The EPA can designate plants with particularly egregious or repeated violations as "High Priority Violators" (HPV). The HPV designation is explicitly "designed to direct scrutiny to those violations that are most important" (EPA 1999, p. 1-1) and, during our time period, is reserved for plants that meet one of ten "general" HPV criteria or five "matrix" criteria. While some violations unambiguously merit HPV designation (e.g., "Failure to obtain a Prevention of Significant Deterioration or New Source Review permit"), others either leave room for regulator discretion (e.g., "Substantial testing, monitoring, record keeping, or reporting violation") or are explicitly dynamic (e.g., "Violation by a chronic or recalcitrant violator"). Once a plant enters HPV status, it triggers a period of intense oversight by the EPA that includes more frequent inspections (which can lead to uncovering additional violations), higher fines, and explicit deadlines for both EPA and plant actions to resolve any outstanding violations. Plants in HPV status face higher regulatory burdens, as shown in Figure 1. As with the Texas example, plants can only exit HPV status after resolving *all* outstanding violations, regardless of whether those violations would independently elevate the plant to HPV status. The combination of increased inspections, violations, fines, and general regulatory oversight means that HPV status is—and is intended to be—substantially costly for plants.

The use of HPV status has been contentious, and the EPA continues to update enforcement policies. During the time frame of our analysis, the EPA used a "watch list" to focus particular attention on HPVs that did not resolve all of their violations in a timely manner. Public disclosure of the watchlist appears to have increased plants' costs by leading to increased attention from local politicians and civilian environmental protection groups (Evans 2016). This is in keeping with evidence from Johnson (2020), who finds that publicizing noncompliance (in that case for OSHA regulations) can be costly to plants. Further, in 2014 (after our sample

[7] While regulatory enforcement can be tailored to individual plants to some extent via adjustments for ability to pay, enforcement is not allowed to vary based on the EPA's perception of plants' underlying costs. In particular, EPA (1991) states on p. 22: "… in order to promote equity, the system for penalty assessment must have enough flexibility to account for the unique facts of each case. Yet it still must produce consistent enough results to ensure similarly situated violators are treated similarly."

period), the guidelines for plants being classified as HPVs were narrowed and the watch list was eliminated. These changes highlight the fact that evaluating the effect of dynamic incentives is particularly important.

B. *General Theoretical Framework*

Our theoretical model of EPA enforcement and plant investment seeks to capture the framework described above in a tractable setting. Our model builds on a literature on rational compliance and optimal punishment (Bentham 1789, Becker 1968). We adopt their view that compliance, in our case with environmental regulations, is a rational decision, where a plant chooses its compliance decisions in order to maximize its surplus.

Landsberger and Meilijson (1982) expand the Becker framework to consider dynamic enforcement in a two-period model of tax compliance. They focus on policies that vary an individual's audit rate (similar to our inspection rate) based on her previous detected violations. Harrington (1988) analyzes dynamic enforcement with a similar framework, where the regulator underpenalizes one-time violations in order to create incentives to avoid repeated violations. Mookherjee and Png (1994) generalize this idea of differential enforcement activities in a static model by formalizing the concept of *marginal deterrence*, where the regulator underpenalizes small violations in order to create strong marginal incentives to avoid large violations. These policies are both examples of what we call *escalation mechanisms*, where marginal deterrence is increasing in the extent of the violation or history of violations.

Most of the theoretical papers on escalation mechanisms show that increasing marginal deterrence can increase surplus given an implicit or explicit cost of penalties or enforcement for the regulator (Landsberger and Meilijson 1982, Harrington 1988, Leung 1991, Mookherjee and Png 1994, Polinsky and Shavell 1998, Friesen 2003). As we noted in Section IA, the EPA faces such costs in enforcing the CAAA. In addition, some studies consider heterogeneous plants and an inability of the regulator to contract on types as a reason for escalation mechanisms (Landsberger and Meilijson 1982, Mookherjee and Png 1994, Raymond 1999, Kang and Silveira 2019). In this case, escalation mechanisms can add value by creating a separating equilibrium across types. For instance, with heterogeneous investment costs, an escalation mechanism may incentivize low-cost plants to invest in pollution abatement when they are regular violators and fines are low while high-cost plants will wait until they become HPVs and fines are higher.

Our model of dynamic CAAA enforcement builds on these insights. Each plant plays a dynamic game with the regulator. Our estimation is consistent with the equilibrium of the game being Markov perfect or with pre-commitment on the part of the regulator.[8] The regulator would like plants to comply with environmental regulations, but also bears a cost from conducting inspections and issuing fines. CAAA violations arise stochastically and plants detect them concurrently with the regulator. Plants make optimizing decisions about whether to invest in remediation of violations. These investments take time and are not always successful in fixing

[8] Pre-commitment is very similar to a plant playing against a "regulatory machine" (as modeled by Duflo et al. 2018).

violations. We allow for an escalation mechanism with dynamic enforcement, as is present in the data. We also allow for heterogeneous plants and an inability to contract on plant type. The underlying reasons for dynamic enforcement are a regulator cost of enforcement; heterogeneous plants; delay and stochasticity in remediation from investment; and imperfect information from inspections.

Each period t corresponds to a quarter and the future is discounted with factor β.[9] Let the *regulatory state* Ω_t be the payoff-relevant state variables over which plant and regulatory actions may depend; Ω_t is known to the regulator and plant at the start of the period.

Each period, the regulator first receives an i.i.d. private information shock to the value of an inspection and then decides whether or not to inspect the plant. Let $\mathcal{I}(\Omega)$ denote the inspection probability and *Ins* the actual inspection decision. The regulator and plant then receive a signal e_t, which provides information on the presence and severity of CAAA compliance issues, including emissions from multiple pollutants, plant reporting concerns, and technology maintenance problems.

Specifically, the signal $e_t \equiv \left(e_t^1, \ldots, e_t^5\right)$, is the predictor of compliance issues beyond the state. It has five potentially correlated dimensions and a joint distribution that depends on *Ins*. First, violations depend on e^1, through the function $Vio\left(\Omega, e^1\right)$. Second, fines depend on e^2, through $Fine\left(\Omega, e^2\right)$. Third, e^3, e^4, and e^5 determine transitions to compliance, regular violator, and HPV status, through $\tilde{\Omega} \equiv T\left(\Omega, e^3, e^4, e^5\right)$. In our framework, $\mathcal{I}(\cdot)$ and $Fine(\cdot)$ are policies chosen by the regulator, whereas $Vio(\cdot)$ and $T(\cdot)$ are dictated by e and CAAA standards.

Following the regulator action, the plant, if not in compliance under $\tilde{\Omega}$, makes a binary decision of whether or not to invest in pollution abatement. Let $X \in \{0,1\}$ denote the investment decision. A plant chooses its investment decision in order to minimize its expected discounted sum of the costs from inspections, violations, fines, designation as a high priority violator, and investment.[10] A plant that invests incurs a cost from its investment, but increases the chance that it returns to compliance in future periods. The regulator chooses its inspection and fine policies to minimize the expected weighted sum of damages from pollution, plant investment costs, and enforcement costs.

In order to further illustrate the value of dynamic enforcement, online Appendix A1 develops a simple, special case of this model, that is similar to Polinsky and Shavell (1998). Our simple case highlights how static escalation mechanisms add value by allowing the regulator to increase the marginal deterrence for multiple violations relative to individual violations. Dynamic escalation mechanisms, including the approach the EPA uses to enforce the CAAA, add more value in theory by allowing the regulator to condition on more variables. The remainder of our paper investigates the extent to which this theoretical result holds in practice, by specializing this model to our empirical context.

[9] While we capture *exogenous* plant exit through the discount factor, with a lower discount factor corresponding to more exit, we do not endogenize exit. Duflo et al. (2018) find no difference in exit rates for plants randomized into additional regulatory scrutiny in India; we believe that plants in our sample are less likely to be at the margin for exit than plants in India.

[10] Since we do not incorporate endogenous exit in our model, we do not model the profit from operations.

II. Data and Empirical Foundations

Before we turn to our empirical framework, Section IIA describes our data sources and Section IIB develops the empirical assumptions that allow us to take our theoretical model to the data.

A. *Description of Data*

Our main analyses principally use four publicly available databases. We summarize our use of the databases here, with details on data construction in online Appendix A2.

Primarily, we use the Environmental Compliance History Online (ECHO) enforcement database.[11] The ECHO database provides plant industry and county, enforcement actions, measures that we use to determine investment, and compliance, regular violator, and HPV status. We infer that a plant has invested if the ECHO data indicate either an environmental issue resolution code or the issuance of a *Prevention of Significant Deterioration* (PSD) permit.[12] Our measure of investment is imperfect in that it only captures large (likely capital) investments rather than smaller investments in improving plant processes that may also reduce pollution. To our knowledge, there is no comprehensive national database that contains these types of smaller process investments. We also collected data from the Texas Commission on Environmental Quality (TCEQ) on all changes in pollution abatement devices at major air polluters in Texas during our time frame (Texas Commission on Environmental Quality 2018) and created a cross-walk from the TCEQ data to the ECHO data (Blundell, Gowrisankaran, and Langer 2020). The TCEQ data confirm that our measure of investment matches well with observed changes in abatement technology.

We collapse the ECHO data from the pollution source (Air Facility System, or AFS, ID) level to the plant (Facility Registry Service, or FRS, number) level using a crosswalk provided by the EPA, and aggregate to the quarter level. We limit our study to the seven most polluting North American Industry Classification System (NAICS) industrial sectors, as listed in Table 2 below. This forms our analysis data, which are at the plant/quarter level and extend from 2007:I until 2013:III.[13]

Table 1 summarizes investment rates by regulatory status. Our data contain 2,355,908 plant/quarter observations. As is well-documented in the literature (e.g., Evans 2016), compliance is high: 95.6 percent of observations indicate compliance. We find that investment occurs in 4.9 percent of quarters when a plant is a violator and in 17.5 percent of quarters when a plant is an HPV. We derive the vast majority

[11] The ECHO database that we use includes eight components (EPA 2014 a,b,c, 2015 a,b,c,d,e). We deflate fines to constant 2007 dollar amounts using the US Consumer Price Index for urban consumers (OECD 2019).

[12] We also infer investments for plants that exited HPV status and eliminate investments in compliance (see Section IIB).

[13] The ECHO enforcement actions data start shortly before the beginning of this period but we start our sample in 2007 to be able to use lagged values of variables. Although this dataset supposedly continued through 2014, we noticed fewer reported cases after 2013:III, which we believe are due to early transitions to the new database. This motivates our choice to end our analysis sample in 2013:III. Our seven industries capture 74 percent of plant/quarters with inspections, 75 percent of plant/quarters with violations, and 78 percent of plant/quarters with positive fines during our sample period, among plants that report to ECHO.

Table 1—Investment Rates by Regulatory Status

	Compliance	Regular violator	High priority violator
Investment (percent)	0.00	4.91	17.50
Investment (from resolution code) (percent)	0.00	4.62	16.35
Investment (from PSD permit) (percent)	0.00	0.34	0.43
Investment (from HPV exit) (percent)	0.00	0.00	0.80
Dropped investment in compliance (percent)	0.37	0.00	0.00
Plant/quarter observations	2,252,570	66,992	36,346

Source: Authors' calculations based on estimation sample.

of these investments (94 percent) from codes that indicate the resolution of an environmental problem. We derive a much smaller set of investments from PSD permits and from exiting high priority violation status. Finally, we observe codes that are indicative of investment in 0.37 percent of plant/quarters in compliance, but do not count these as investments.

Not shown in the table, our data cover 107,705 unique plants, of which 66.7 percent are present in every quarter of our sample period. Compliance is also high when considering individual plants: 88.4 percent of plants are never out of compliance, while 7.4 percent of plants have at least one quarter in which they are a regular violator but are never in HPV status. Only 4.2 percent of plants have at least one quarter in which they are in HPV status.

We combine the ECHO enforcement data with three additional datasets. First, the National Emissions Inventory database measures emissions every three years (EPA 2019). Our study focuses on emissions of criteria air pollutants (and not hazardous air pollutants) as the data quality for these pollutants is much better (EPA 1997). We merge the 2008 and 2011 NEI data from ECHO's Air Emissions Data to our base data using the FRS number and year. We use the NEI data in combination with the AP3 data described next to understand each plant's expected gravity of a violation. Further, we use the NEI data to calculate the mean levels of six pollutants by regulatory state, which are necessary for our counterfactuals.

Second, we use the AP3 database (Clay et al. 2019) for elevated (e.g., smokestack-level rather than ground-level) emissions to get the marginal damages for criteria air pollutants in each county in 2011. We supplement the AP3 data with a national estimate of the marginal damages of lead from Zahran et al. (2017).[14]

Third, the National Ambient Air Quality Standards (NAAQS) database indicates whether a given county is entirely or partly in non-attainment of NAAQS during our sample period (EPA 2018). These data enter into our measure of the expected gravity of a violation.

Table 2 provides summary statistics on the reported criteria air pollution damages for our analysis data, by industry. There is substantial variation in the pollution damages across industries. For plants in compliance, the most (least) polluting

[14] Zahran et al. (2017) measure the effect of leaded aviation fuel on the level of lead in children's blood and associate this with changes in long-run earnings. This is likely a lower bound on the marginal damages of lead (Hollingsworth and Rudik 2019).

Table 2—Summary Statistics on Mean Criteria Air Pollution Levels

Industry	Observations in analysis data	Mean level in compliance	Mean level as regular violator	Mean level as HPV
Mining and extraction (NAICS 21)	687,400	$500	$3,997	$5,138
Utilities (NAICS 22)	112,554	$14,937	$60,656	$97,472
Manufacturing: food, textiles (NAICS 31)	139,826	$642	$2,981	$4,090
Manufacturing: wood, petroleum (NAICS 32)	617,572	$895	$2,832	$6,422
Manufacturing: metal (NAICS 33)	539,000	$319	$2,020	$3,655
Transportation (NAICS 48)	157,326	$414	$1,117	$3,228
Educational services (NAICS 61)	132,209	$662	$1,844	$2,840

Note: Table reports summary statistics on total criteria air pollution damages in thousands of dollars per plant/quarter observation in our analysis data.

industry in our data is utilities (educational services). Across industries, average pollution damages are highest for plants in HPV status and lowest for plants in compliance.

B. *Empirical Foundations of the Estimable Model*

Recall that in our dynamic model, the plant's decisions are a function of its regulatory state. In principle, the regulatory state lists the plant's history of prior violations and investments and its EPA region, industrial sector, and expected gravity of violations. In practice, we need to summarize this information for tractability. In this section we provide evidence to motivate our state space and other modeling choices, with further substantiating tables and figures in online Appendix A4.

Investment.—We first investigate the role of current and past investment in affecting violator status by regressing whether a plant returns to compliance (from regular or high priority violator status) on current investment, and four quarter lags of investment. We find that investment in the previous quarter is a very strong predictor of a return to compliance, increasing the probability of a return by 38 percentage points. Investment two quarters ago is a weaker, though still statistically significant and positive predictor. In contrast, current investment, and further lags of investment are all negative predictors.[15] Based on these regressions, our state space allows for two lags of investment to affect the regulatory state. We also assume that current investment does not impact a plant's likelihood of returning to compliance in the current period (but can in the subsequent two periods). Finally, the lack of a positive current effect of investment motivates our timing assumption that investment occurs at the end of each period, after the regulator's actions and regulatory outcomes.

Focusing now on investment in the previous quarter, Figure 2 shows in more depth the frequency with which this investment resulted in a return to compliance. If the plant starts the period in HPV status and did not invest in the previous quarter then it will, with certainty, finish the quarter in HPV status. If the plant did invest, there is still a 25 percent chance that it will finish the period in HPV status, but there is now a

[15] The negative coefficient on current investment may be due to plants in violation investing when additional problems arise.

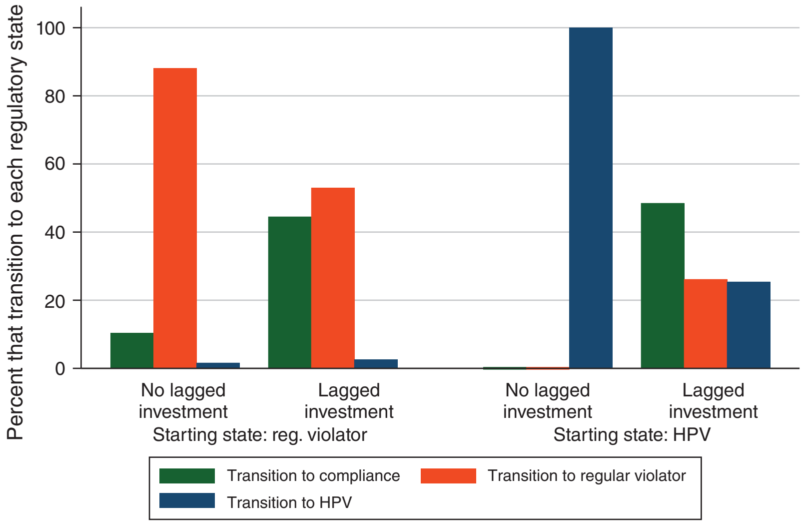

FIGURE 2. EFFECT OF INVESTMENT ON REGULATORY STATE

Source: Authors' calculations based on estimation sample.

49 percent chance that the plant will transition to compliance and a 26 percent chance that the plant will transition to regular violator status. Lagged investment similarly increases the rate at which the plant transitions from regular violator status to compliance, although some plants do transition from regular violator status to compliance even without investment. Thus, overall, investment increases the probability that a plant returns to compliance, but does not result in compliance with certainty.

Finally, we consider investments in compliance, to investigate whether these might help prevent future violations. We estimate whether a plant transitions out of compliance given recent investment, region, industry, and gravity state dummies. We find that investments in compliance *increase* the likelihood that a plant transitions to both regular and high priority violator status in the following two quarters.[16] We therefore assume that any investments that we observe in our data that occur while a plant is in compliance are economic investments (e.g., designed to increase productivity) rather than prophylactic efforts to improve environmental compliance.

Depreciated Accumulated Violations.—Figure 1 showed that inspections, violations, and fines all varied substantially based on whether the plant is in compliance, a regular violator, or an HPV. We further investigate, within these categories, whether previous violations are predictive of inspections, violations, and fines. We define a summary measure for plants out of compliance called "depreciated accumulated violations" which is the sum of the depreciated violations from the previous quarter back to the period the plant most recently left compliance. We find that for

[16] This result is consistent with the evidence presented in Keohane, Mansur, Voynov (2009) that shows that the EPA was more likely to bring lawsuits against plants with recent large (economic) investments, a result that they attribute to increased regulatory scrutiny after major investments.

both regular and high priority violators, depreciated accumulated violations is a strong and positive predictor of inspections, the probability of having a positive fine, and violations.[17] We therefore include depreciated accumulated violations as a state variable that can affect plants' expected regulatory burden.

Gravity State.—As we discussed in Section IA, one of the key components of the EPA's determination of fines is the gravity of the associated violation. The gravity of a violation is primarily determined by its actual or potential harm, which varies with the pollutants emitted and plant location. Gravity is not directly recorded in the ECHO database.[18]

We construct a version of plant-specific expected gravity that aims to capture plants' expectations of the actual and potential harm of a violation as well as the regulatory scrutiny brought about by a plant being in a NAAQS non-attainment area.[19] We focus on the idea that the distribution of pollution across plants in an industry forms the basis of expectations about pollution quantities, both in terms of the mean amount of pollution and the extreme level of pollution if it were an outlier in its industry.

For a given plant in a given county, we therefore take every plant in the same industry nationally, and use the NEI pollution database and the AP3 damages database to calculate the damages from criteria air pollutants if each of those plants were located in this county. From this distribution, we take the mean of this distribution as the plant's expected actual damages of a violation and the ninetieth percentile of this distribution as the expected potential damages of a violation. We then combine this information with the NAAQS non-attainment database to sort plants into five gravity state bins: below and above the national median for actual and potential damages, further splitting those above the median in both categories into attainment and non-attainment status during our sample period.

Heterogeneity in Regulatory Environment and Costs.—Our model allows plants to find both regulatory policies (inspections and fines) costly. We assess how these enforcement decisions vary across different regions and industries by measuring the ratio of fines in HPV status to regular violator status and correlating these ratios with the analogous ratios of inspection rates. We find a correlation of 0.06 ($p = 0.87$) across regions and 0.09 ($p = 0.86$) across industries. These low correlations imply that regions and industries differ in how enforcement escalates with the regulatory state, which will help us identify the costs of fines separately from the costs of inspections.

[17] We use a 10 percent quarterly depreciation rate for accumulated violations, as this results in better predictors for these variables than other depreciation rates.

[18] While the data do include the pollutant implicated in the violation, this field is only reported for 14.6 percent of violations because it does not fall under the federal minimum data requirements of what must be reported to the EPA for every plant. Further, when the "pollutant" is reported, it is often a generic entry such as "facility-wide permit violations" (conditional on an entry, 34.8 percent of pollutants list this code).

[19] Our measure of non-attainment is whether a county is in non-attainment for any pollutant during any year of our sample period. In our data, 87 percent of counties are either fully in attainment or out of attainment for at least one pollutant in every year of our sample period and only 1.6 percent are out of attainment for a minority of years, implying that this is a reasonable and computationally tractable approximation.

Finally, our data exhibit substantially more serial correlation in investment than we would expect to occur randomly. About 30 percent of investments are followed by at least one additional investment within the next six quarters, relative to the approximately 2.3 percent we would observe if investment were i.i.d. This suggests that a random coefficients model may be important.

III. Empirical Framework

This section specializes the model we developed in Section IB to our empirical context, presents our estimation approach, and discusses identification. Online Appendix A3 provides additional details.

A. *Estimable Model*

We do not estimate the regulator's utility function. Rather, we specify the regulator's policy function as CCPs (Aguirregabiria and Mira 2007), and then use the regulator's CCPs to estimate plants' utility functions. Following the evidence in Section IIB, we let the regulatory state Ω have six components: (i) EPA region, (ii) two-digit NAICS industrial sector, (iii) expected gravity of potential violations, as measured by county non-attainment status and potential environmental damages for plants based on county and industry, (iv) depreciated accumulated violations with a 10 percent quarterly depreciation rate, (v) regular violator or high priority violator status, and (vi) two quarterly lags of investment.

The regulatory state needs to capture all information that affects the distribution of current and future regulatory actions in order for plants to have the same priors on expected regulatory enforcement as our model. Formally, we impose the following.

ASSUMPTION 1: *The environmental compliance signal at period t, e_t, is a function only of the regulatory state Ω_t, the regulator inspection CCPs $\mathcal{I}$, and the inspection decision Ins_t.*

Assumption 1 imposes that e is a function of the regulatory state and the regulator's inspection policy and decision. It rules out the possibility that an investment that is not in the regulatory state (for instance one that occurred many periods ago) could change e. We keep two lags of investment in the regulatory state, and both are allowed to affect the compliance signal.

Assumption 1 is stronger than what we require for estimation: for estimation, we could have directly assumed that plants' have priors on violations, fines, and transitions based only on Ω and the inspection decision, rather than assuming that the underlying signal is a function of Ω and other information. However, Assumption 1 is critical for our counterfactual experiments because it makes explicit how plants' priors will change under different regulatory regimes: it implies that a plant at a given regulatory state Ω_t faced with a given inspection decision and inspection policy will face the same distribution of e—and hence the same distribution of violations and transitions—even under counterfactual fine policies.

Note that e depends on the inspection policy in addition to the regulatory state and the inspection decision. Our conditioning of e on the inspection policy allows the frequency of inspections to affect the expected distribution of signals, which we believe adds to the credibility of our counterfactuals. However, it also implies a limitation of our potential counterfactuals: changing the regulator's inspection policy may change the distribution of e in ways we cannot observe. This limits us to changing the fine policy but not the inspection policy in our counterfactuals.

We let the flow utility for the plant from regulatory actions be

$$U(\Omega, e) = \theta^I Ins(\Omega) + \theta^V Vio(\Omega, e^1) + \theta^F Fine(\Omega, e^2) + \theta^H HPV\big(T(\Omega, e^3, e^4, e^5)\big), \tag{1}$$

where $HPV(\cdot)$ denotes HPV status designation, and $\theta^I, \theta^V, \theta^F$, and θ^H are parameters. Note that (1) implies that plants can have a cost from not only fines, but also inspections, additional violations, and being an HPV (consistent with the evidence in Section IA), though not from regular violator status.

Recall that once the pollution signal is revealed and regulatory actions are complete, the state is $\tilde{\Omega}$, and the plant can invest if it is not in compliance. Our data are at the level of the plant/quarter and include a panel of plants observed over time. For each plant/quarter, we observe the regulatory state at the point where the plant makes its investment decision—which is $\tilde{\Omega}$—and its investment decision. The cost of investment is $\theta^X + \varepsilon_{Xt}$. Both ε_{0t} and ε_{1t} are idiosyncratic cost shocks. We assume that these shocks are i.i.d., known to the plant prior to making its investment decision, and distributed type 1 extreme value. Plants that are in compliance receive a single shock ε_{0t} and do not make any active decision.

Group together the structural parameters as $\theta \equiv (\theta^I, \theta^V, \theta^F, \theta^H, \theta^X)$. We generally expect these parameters to be negative, except for θ^X, which we expect to be positive. We assume that θ is fixed for the plant over time. In our estimated model, θ will vary across plants. We assume that θ is not contractable, i.e., the regulator cannot choose different enforcement contracts for different plants based on θ.

B. *Estimation of Regulator CCPs*

We estimate plants' expectations of regulator actions, which are *Ins*, *Vio*, *Fine*, and T, with CCPs. We specify inspections as a probit of the plant's state Ω. The remaining CCPs are a function of the state Ω, whether an inspection occurred, and the signal e. Econometrically, $(e^1, \ldots, e^5)$ are the residuals in the latent predictors for these CCPs.

We allow for $(e^1, \ldots, e^5)$ to be correlated. Rather then estimating *Vio*, *Fine*, and T jointly, we estimate the marginal density of *Vio*, the conditional density of *Fines* given whether a violation occurred (by including this variable in the regression), and the conditional density of T given the fines assessed and whether a violation occurred. To condition on the state, we estimate the CCPs separately for plants in compliance, regular violators, and HPVs and include indicators for two lags of investment; region, industry, and gravity state dummies; and depreciated accumulated violations (for plants not in compliance). We estimate *Vio* with a probit, *Fine* with a Tobit, and T with multinomial logits. Our CCPs include interactions of inspection and gravity state except in cases where this led to convergence problems.[20]

C. *Empirical Implementation of Random Coefficients Model*

Our model allows for the parameter vector θ to differ across plants.[21] Specifically, we assume that θ for each plant takes on one of a fixed set of values $(\theta_1, \ldots, \theta_J)$ and that each parameter vector θ_j, $j = 1, \ldots, J$, occurs with probability η_j. Each plant receives a single, independent draw of θ from the multinomial distribution of potential values. The structural parameters that we estimate are therefore $\eta \equiv (\eta_1, \ldots, \eta_J)$ and not $(\theta_1, \ldots, \theta_J)$. We impose no restriction on the structural parameters other than what is necessary based on the fact that they are population probabilities:

$$(2) \qquad \sum_{j=1}^{J} \eta_j = 1 \quad \text{and} \quad 0 \leq \eta_j \leq 1, \ \forall j.$$

Econometrically, the values of $(\theta_1, \ldots, \theta_J)$ are taken as given. We take a (large) fixed grid of these values, meant to capture the range of plausible parameter values.

We estimate the parameters by adapting the methods of Fox et al. (2011) and Nevo, Turner, and Williams (2016). Specifically, this framework leads to a computationally quick and convex GMM estimator, allowing us to estimate many parameters and approximating a nonparametric density over the θ utility parameters (Fox, Kim, and Yang. 2016).

Our GMM estimator has the form $\eta^* = \mathrm{argmin}_\eta \|G(\eta)\| = \mathrm{argmin}_\eta G'(\eta) W G(\eta)$, where $G(\eta)$ is a $K \times 1$ vector of moments, G' is the transpose of G, and W is a weighting matrix. Each individual moment $G_k(\eta)$, $k = 1, \ldots, K$, can be written as the difference between the value of some statistic in the data, m_k^d and the weighted sum of the value of the statistic for the parametrized model, $m_k(\theta_j)$, where the weights are $\eta_1, \ldots, \eta_J$:

$$(3) \qquad G_k(\eta) = m_k^d - \sum_{j=1}^{J} \eta_j m_k(\theta_j).$$

We compute each m_k^d and $m_k(\theta_j)$ in an initial stage, before estimating η^*. This requires solving the relevant Bellman equation and $m_k(\theta_j)$ for each of the J grid parameters. Using these values, we then estimate η^* by minimizing $\|G_k(\eta)\|$ subject only to the constraints in (2). We perform a two-step process to improve the efficiency of the weighting matrix W.

Because we do not see plants from their inception onwards, we need to make an assumption about the likelihood of seeing each plant in any of its possible states. First, define a division of the state $\tilde{\Omega}$ into $\tilde{\Omega}^1$—which indicates the fixed states of region, industry, and gravity state—and $\tilde{\Omega}^2$—which indicates the variable states of compliance status, lagged depreciated accumulated violations, current violation, and lagged investments. Using this definition, we make the following assumption for our random coefficients estimation.

[20] Online Appendix A4 provides marginal effects for the CCPs. In general, the results match our expectations.
[21] In addition to our random coefficient model, we estimate a homogeneous coefficients model.

ASSUMPTION 2: *The observed data reflect plants that are at the steady state distribution of* $\tilde{\Omega}^2$ *conditional on a given* $\tilde{\Omega}^1$.

Assumption 2 would be valid if, for instance, plants enter at randomly distributed points from the steady state distribution of $\tilde{\Omega}^2$ given $\tilde{\Omega}^1$. It would also occur if they have been active a long time, in which case the distribution of $\tilde{\Omega}^2$ for any θ_j value would approach its steady state distributions. It rules out a situation where all plants are still adapting to a new regulatory regime.

We compute three sets of specific moments using Assumption 2. Each moment in the first set indicates the equilibrium share of being at a particular time-varying state, conditional on $\tilde{\Omega}^1$. Each moment in the second set indicates the conditional equilibrium share of plants at a particular time-varying state times the share investing at this state. These moments all follow closely from Nevo, Turner, and Williams (2016). Our third set of moments explicitly uses our panel data: each multiplies a second set moment by the corresponding sum of investments in the following six periods. As in Nevo, Turner, and Williams (2016), we obtain inference for our parameters and counterfactuals by bootstrapping, with resampling at the plant level.[22]

We fix $\beta = 0.95^{1/4}$ per quarter. This incorporates both time-discounting at the quarterly rate of 0.0098 and an exogenous probability of exit, which is 0.0031 per quarter in our data.

D. *Identification*

To understand how the utility parameters θ in our model are identified, consider first a two-parameter version of the homogeneous coefficients model where plants find investment and fines costly but do not face costs from inspections, violations, or HPV status and where the idiosyncratic investment cost shocks are zero. In this model, at any violator state, a plant would observe its expected change in discounted future fines conditional on investment. If investment reduced expected discounted future fines by more than the cost of investment, then the plant will invest. Therefore, if the ratio of investment costs to fine costs, $\theta^X/-\theta^F$, was less than the expected change in future fines, the plant would invest. Under this simple model, the parameter ratio is identified from the lowest expected change in future fines at which plants invest.

Conditional on having identified the ratio of the two parameters, we can identify the scale of the parameters by adding in the type 1 extreme value investment cost shocks. The scale is identified by the rate at which the investment probability increases with the expected change in future fines. The steeper is this rate, the larger is this scale.

Our actual model includes five parameters per plant, which capture four dimensions of regulatory costs borne by the plant, plus the cost of investment. Thus, to identify this model, we need independent variation in how investment changes the expected future level of each of these four dimensions. While there is some variation

[22] In order to facilitate coding our estimation algorithm, we created a class assignment based on this paper. We placed the assignment at https://doi.org/10.5281/zenodo.3724953.

in these changes for different states, $\tilde{\Omega}^2$, within a region, industry, and gravity state, the additional variation across these fixed states, $\tilde{\Omega}^1$, is very helpful in identifying these parameters.

This identification argument hinges on accurately measuring plants' expectations of future regulatory actions with and without investment. We calculate these expected regulatory actions using the estimated regulator's CCPs and future actions of the plant. For these CCPs to be valid in the context of our model, we need plants to not have private information about future regulatory actions and outcomes beyond the functions that we estimate. If this assumption did not hold, this would lead to serially correlated unobserved state variables, invalidating our Assumption 1 and requiring very different estimation methods. Our specifications all include fixed effects by region, industry, and gravity state as well as a variety of interactions in order to accurately capture plants' beliefs.

Our random coefficients model requires an additional identification argument since we must identify the distribution of values of θ rather than just the mean values of these parameters. If some plants repeatedly invest while other plants in the same state invest very infrequently, this would suggest variation in investment costs. More generally, persistence in decisions over time beyond what can be explained by the Markovian structure of the dynamic model with a single θ will identify heterogeneity of types. Persistence implies that more heterogeneity will lead to a higher occurrence of extreme states, e.g., many plants in HPV status and many plants in compliance.

We identify the distribution of regulatory costs even though, in our data, the substantial majority of plants never leave compliance. Our model assumes that leaving compliance is not a function of the plant's type, θ. This allows us to identify the distribution of random coefficients based only on the behavior of plants not in compliance.

Our model chooses parameters that most closely match the steady state equilibrium dispersion across states and investment rates in those states to data. We also match the serial correlation in investment in the data with our third set of moments. The greater the correlation here, the more cost heterogeneity we would expect.

Finally, our investment variable captures large investments rather than small process investments, since the latter are not available in our data. Our model implicitly captures these process investments through their impact on expected future fines, but it does not endogenize them. In other words, it does not allow them to vary in counterfactual policy environments. If plants invest more in these processes when they are faced with higher marginal enforcement, we would understate the importance of dynamic enforcement.

IV. Results

A. *Model Estimates*

We provide structural parameter estimates in Table 3 for our main model and a homogeneous coefficients specification estimated via quasi-maximum likelihood.[23]

[23] We calculate a quasi-likelihood (and not a likelihood) because we use the regulator's estimated CCPs in the plant's dynamic optimization process.

Table 3—Estimates of Plants' Structural Parameters

	Quasi-likelihood estimates	GMM random coefficient estimates					
		(1)	(2)	(3)	(4)	(5)	(6)
Negative of investment cost ($-\theta^X$)	−2.872	−2.334	−1.326	−2.498	−2.540	−1.988	0.153
	(0.041)						
Inspection utility (θ^I)	−0.049	−0.194	0.444	−0.096	0.897	0.001	−2.483
	(0.049)						
Violation utility (θ^V)	−0.077	0.143	0.128	0.650	−0.100	−2.169	−2.006
	(0.197)						
Fine utility (millions \$, θ^F)	−5.980	−5.181	−6.073	−6.766	−8.460	−7.494	−7.524
	(1.005)						
HPV status utility (θ^H)	−0.065	−0.029	−0.234	−0.078	−0.411	0.070	−2.437
	(0.015)						
Weight on parameter vector	1	0.438	0.174	0.170	0.126	0.049	0.019

Notes: For the quasi-likelihood approach, we estimate the costs themselves, whereas for the GMM random coefficient approach, we estimate the weights (in the bottom row) on each potential vector of costs. For GMM estimates, we report the six parameter vectors with the highest weight. Standard errors for quasi-likelihood estimates, which are bootstrapped with resampling at the plant level, are in parentheses.

The table reports utility parameters as well as the probability that a plant has each of those utility parameters. For the quasi-likelihood model, since there is one set of coefficients, this probability is 1, and we report bootstrapped standard errors. For the random coefficient estimates, however, we allow the parameter vectors θ to be chosen from a wide grid of potential values. We report the estimated probability, η_j, of observing each of the parameters, θ_j, in the last row of Table 3. We report the six θ_j parameters with the highest probabilities η_j, and we list the θ_j parameters in descending order of η_j. We do not report standard errors for this specification as it would be difficult both to calculate them and to interpret them meaningfully, given that most of the estimated weights are 0. Instead, we report bootstrapped standard errors for our counterfactuals below.

We start with the quasi-likelihood results, which are on the left of Table 3. We find that investments, inspections, violations, fines, and being in HPV status are all costly for plants, with statistically significant effects for investments, fines, and HPV status.[24] This is consistent with Duflo et al. (2018), who find that both regulation and investment in pollution abatement are costly to plants.

We next turn to the GMM random coefficients estimates. This specification estimates that six values of θ account for nearly 98 percent of plants.[25] Nearly one-half (44 percent) of the weight is on a set of coefficients that are similar to the quasi-likelihood coefficients. Given that we are estimating utility parameters, we consider the ratios of coefficients. In particular, for plants of this type, investments are equivalent to a \$450,000 fine (2.334/5.181 multiplied by \$1 million), HPV status is equivalent to a \$5,600 fine per quarter, and each inspection is equivalent to a \$37,400 fine. Unlike for the quasi-likelihood estimates, violations increase utility

[24] We report the negative of the investment cost, so a negative θ^X implies costly investment.

[25] Heiss, Hetzenecker, Osterhaus (2019) note that this estimator is similar to a LASSO and hence may generate a small number of positive parameters due to an implicit penalization of additional positive parameters.

slightly, which means that for these plants, violations do not themselves lower utility, although they do positively correlate with transitions to HPV status.

While it is straightforward to discuss the relative magnitude of our coefficients, understanding their absolute magnitude is complicated by the fact that fines may be costly to a plant beyond just the amount assessed by the EPA. Resolving fines likely involves additional legal work for the plant and harm its reputation more broadly (as Evans 2016 and our estimates suggest HPV status does). This would imply that the cost to a plant of a \$1 fine may be substantially larger than \$1, which would in turn imply that if an investment is equivalent to \$450,000 in fines, then it may actually cost the plant substantially more than \$450,000 to invest.

One way to evaluate the potential absolute magnitude of our coefficient estimates is to compare our estimates of investment costs to estimates from the literature on the cost to plants of pollution abatement capital expenditures. Becker (2005) uses the US Census Bureau's Pollution Abatement Costs and Expenditures (PACE) survey to get estimates of average air pollution abatement capital expenditures per plant given non-zero outlays. In 2007 dollars, he finds that these expenditures average \$1.1 million and argues that these are an understatement of the true cost because regulatory compliance may necessitate production process changes that are costly and because the PACE survey does not include the cost of permits or sacrificed output. Dividing \$1.1 million by our \$450,000 estimate of the investment costs relative to fines suggests that the true cost to a plant from the imposition of a dollar of fines is \$2.4, with correspondingly higher monetary costs for other regulatory actions. Because Becker (2005) views his estimates as a lower bound on the cost of investment, we assume a \$1 fine is equivalent to \$3 in costs in some counterfactuals.

Interestingly, the second most common set of coefficients, with 17 percent weight, has much lower investment costs (equivalent to a \$218,300 fine) and higher HPV costs (equivalent to a \$38,500 fine per quarter). These plants find inspections beneficial.[26] In fact, across the five most common coefficient estimates, which represent 95.7 percent of plants, the plants with the highest HPV costs and lowest investment costs are the ones that find inspections beneficial.

Column 6 of Table 3 shows that 1.9 percent of plants have a small but negative mean cost (or benefit) of investment (equivalent to a −\$20,300 fine per investment). Note that these plants have extremely high costs of inspections (equivalent to a \$330,000 fine), violations (a \$266,600 fine), and HPV status (a \$323,900 fine per quarter), and may be very adverse to environmental enforcement activities relative to investment.

For the five coefficients with the most weight, representing 95.7 percent of plants, the GMM investment costs relative to fine costs range from \$218,000 to \$450,000. This range is much smaller than the range in other regulatory enforcement coefficients relative to their means. For instance, HPV costs relative to fine costs range from −\$9,300 to \$48,600 per quarter for these plants. Thus, the GMM coefficients suggest that there is more heterogeneity in plants' HPV, inspection, and violation cost than there is in plants' investment costs.[27]

[26] This is in keeping with Duflo et al. (2018), who find that inspections can be beneficial to plants.

[27] Online Appendix A4 provides evidence on model fit and sensitivity checks in which we estimate our model for a single industry, for the ten most populous states (with state fixed effects in the CCPs instead of region fixed effects), and with richer CCPs.

B. *Counterfactuals*

Using the coefficient estimates from Table 3, we now model how EPA enforcement activities, plant investments, overall compliance, and air pollution damages would change under different EPA policies. Because we do not recover regulator preferences, our counterfactuals are based on plant optimization given alternative regulatory policies and do not necessarily stem from the equilibrium of a dynamic game. As we discussed in Section IIIA, we limit our counterfactuals to ones with the same state-contingent inspection policy and only vary the state-contingent fine policy and plants' structural parameters.

We conduct two sets of counterfactual policies. Our first set evaluates the value of dynamic enforcement. Here, we first examine how outcomes would change if the regulator fined all plants in regular and high priority violator status identically for a given region, industry, and gravity state, keeping *total assessed fines* the same as the baseline for each such group. We compare this to a similar counterfactual where the regulator fined all plants in regular and high priority violator status identically for a given region, industry, and gravity state, but where it kept *total pollution damages* the same as the baseline within each group.[28] Finally, we consider a counterfactual where the fines for plants in HPV status are doubled, thereby *increasing* the escalation rate of fines.

Table 4 presents the results of these counterfactual experiments. We report the long-run mean values of regulatory states, regulatory actions, investment rates, plant utility, and pollution damages.

Column 1 of Table 4 reports the observed rates of each outcome in our data, while column 2 reports the baseline, which is calculated at the estimated parameters. In general, our model reproduces the data well: the frequency at which plants are in each regulatory state, the investment, inspection, and violation rates, and the mean pollution damages are similar. Assessed fines are slightly higher in the baseline than in the data.

Column 3 of Table 4 reports the non-dynamic case when equilibrium total fines are the same as in the baseline. We find large increases in the share of plants in HPV status and in pollution damages. In particular, we find that the share of plants in HPV status would rise from 1.4 percent to 30.8 percent. This increase comes mostly from a reduction in the share of plants in compliance and is matched by an increase in regulator workload from a higher inspection rate (from 9.4 percent to 20.5 percent of plant/quarters) and violation rate (from 0.54 percent to 5.0 percent). However, the investment rate drops only moderately (from 0.54 percent to 0.47 percent of periods), suggesting that the heterogeneity in the types of plants that invest and the timing of their investment is important. Finally, given the much higher level of plants in HPV status, we also find much higher levels of air pollution damages. Specifically, damages from criteria air pollutants rise from \$1.5 million per plant/quarter to \$4.0 million per plant/quarter, an increase of 164 percent. This provides strong evidence that dynamic fines are effective in lowering pollution damages, conditioning on the fine level.

[28] For these counterfactuals, we assume that the regulator never fines plants when they are in compliance, and we set the cost of HPV status to zero to fully remove dynamic enforcement.

TABLE 4—COUNTERFACTUAL RESULTS: CHANGING THE ESCALATION RATE OF FINES

	Data (1)	Baseline (2)	Same fines for all violators; fines constant (3)	Same fines for all violators; pollution damages constant (4)	Fines for HPVs doubled relative to baseline (5)
Compliance (percent)	95.62	95.11 (0.22)	66.72 (13.91)	94.49 (0.62)	95.52 (0.24)
Regular violator (percent)	2.88	3.47 (0.25)	2.53 (0.57)	2.72 (0.56)	3.47 (0.26)
HPV (percent)	1.50	1.42 (0.05)	30.75 (14.43)	2.79 (0.65)	1.01 (0.03)
Investment rate (percent)	0.40	0.54 (0.05)	0.47 (0.06)	0.65 (0.09)	0.55 (0.05)
Inspection rate (percent)	9.65	9.41 (0.06)	20.54 (5.41)	9.88 (0.23)	9.28 (0.05)
Fines (thousands $)	0.18	0.32 (0.03)	0.32 (0.03)	1.98 (1.62)	0.36 (0.03)
Violations (percent)	0.55	0.54 (0.01)	5.00 (2.20)	0.74 (0.10)	0.49 (0.01)
Plant utility	—	0.006 (0.034)	0.077 (0.091)	0.001 (0.039)	0.005 (0.034)
Pollution damages (milions $)	1.65	1.53 (0.03)	4.04 (1.19)	1.53 (0.03)	1.48 (0.02)

Notes: Each statistic is the long-run equilibrium mean, weighting by the number of plants by region, industry, and gravity state in our data. Plant utility reports the average flow utility across types and states including ε except for Euler's constant. Column 1 presents the value of each statistic in our data. Column 2 presents the results of our model given the estimated coefficients and the existing regulatory actions and outcomes. Other columns change the state-contingent fines and the HPV cost faced by plants. Columns 3 and 4 impose the same fines for all regular and high priority violators for a given fixed state. Column 5 doubles the fines for plants in HPV status. All values are per plant/quarter. Bootstrapped standard errors are in parentheses.

Column 4 of Table 4 also removes the escalation of fines with regulatory state, but now holds pollution damages within region, industry, and gravity state constant while allowing fines to vary. We find a slightly higher share of plants in HPV status (2.8 percent versus 1.4 percent) with a related slight increase in the inspection and violation rates and a slight increase in the investment rate relative to the baseline. What is striking, however, is that mean fines increase by 519 percent, from $320 per plant/quarter to $1,980 per plant/quarter.[29] To the extent that the regulator bears costs from imposing fines, this result shows that the regulator would find it quite costly to have fine policies that do not escalate across regulatory states.

Finally, column 5 of Table 4 doubles the fines for plants in HPV status from their baseline level. This decreases the share of plants in HPV status from 1.42 percent to 1.01 percent, while simultaneously decreasing the inspection and violation rates and increasing the investment rate slightly. With this fine policy, average pollution damages drop from $1.53 million to $1.48 million per plant/quarter. We take this as evidence that while there is some benefit to increasing the rate at which fines escalate with regulatory status, this benefit is limited.

We replicate these counterfactuals for the quasi-likelihood coefficient estimates in online Appendix A4. The effects of dynamic enforcement are larger under the random coefficients model, demonstrating that heterogeneous plant types (with an inability to contract on plant type) adds to the value of dynamic enforcement.

Our second set of counterfactuals evaluates how escalation mechanisms relate to policies that charge each plant in regular or high priority violator status for its additional pollution damages relative to compliance, much like a Pigouvian tax (Pigou 1947).[30] Charging plants according to their pollution damages is efficient in a world where the regulator does not care about inspection costs or imposing

[29] The 90 percent confidence interval is [$1,465, $6,750], well above the baseline level.

[30] As with the counterfactuals that removed dynamic enforcement, these counterfactuals assume that the regulator never fines plants when they are in compliance and that plants face no direct cost of HPV status.

fines.[31] These Pigou-style policies have two fundamental differences with current EPA policies. First, to increase the marginal deterrence of HPV status, existing fines escalate much more steeply with regulatory state than pollution damages,[32] while Pigou-style policies do not escalate in this way. Second, Pigou-style policies lower pollution damages by allowing for higher fines for industries that are more polluting. Because we believe that some of the cost to plants of fines could be non-monetary, we conduct this experiment in two ways: (i) where the fine cost to plants is entirely monetary, so the efficient fine is the full damages, and (ii) where the fine cost to plants is three times the imposed fine (following our discussion of Becker 2005), so the efficient fine is one-third of the damages. Finally, our third counterfactual escalates fines at the same rate as pollution damages, but scales them to keep aggregate pollution damages the same as the baseline.

Table 5 presents the results of these experiments. Focusing on column 2, Pigouvian fines where the fine cost to plants is entirely monetary are extremely large: 173 times higher than in the baseline at \$55,240 per plant per quarter. Even with this massive increase in fines, the share of plants in HPV status actually increases from 1.4 percent to 1.7 percent. Importantly, the share of plants in regular violator status drops substantially, from 3.5 percent to 1.6 percent. This is consistent with the theory on escalation mechanisms (Mookherjee and Png 1994): dynamic enforcement “underdeters” one-time violations in order to increase the marginal deterrence for repeat violations. Further, Pigouvian fines lead to a 13.7 percent reduction in pollution damages (from \$1.53 million to \$1.32 million per plant per quarter), so the dynamic enforcement approach leads to inefficiently high pollution damages if it were costless for the regulator to impose fines and the fine cost to plants was entirely monetary. Column 3 reports analogous figures where Pigouvian fines are scaled by one-third. It shows similar results to column 2.

Finally, column 4 of Table 5 displays the outcome if we set fines so that they escalate from regular violator to HPV at the same rate as damages, but are scaled so that total pollution damages across all regions, industries, and gravity states is unchanged from the baseline.[33] These results demonstrate the value of dynamic enforcement: with scaled Pigouvian fines, average fines are 394 percent higher,[34] the share of plants in HPV status is 934 percent higher, and inspections increase by 51 percent, relative to the baseline.

In order to evaluate the impact of our counterfactuals across industries, Table 6 shows how four of our counterfactual fine structures affect fines, pollution damages, and regulatory status for three representative industries: mining, utilities, and metal (and related) manufacturing. Column 1 recreates our baseline results, this time separately for each of the three industries, with the other columns replicating columns 3 and 4 of Table 4 and columns 3 and 4 of Table 5. Focusing on column 2—which

[31] Note also that the EPA’s mandate is not to achieve the efficient level of pollution but rather to enforce the CAAA. Explicitly, the EPA may assess civil and administrative penalties for violations under Section 113(b) of the Clean Air Act Amendments. Since the CAAA set specific definitions of a violation, this enforcement behavior can differ substantially from a Pigouvian tax even apart from a disutility on fines.

[32] Actual fines are approximately 13 times higher in high priority violator status than in regular violator status (Table 1) while damages are only 1.7 times higher (the weighted mean from Table 2).

[33] In order to recover pollution damages that are the same as the baseline but with fines escalating at the same rate as Pigouvian fines, we divide the Pigouvian fines by 168.

[34] The 90 percent confidence interval is [\$445, \$3,950], which is above the baseline level.

Table 5—Counterfactual Results: Scaled Pigouvian Fines

	Baseline (1)	Pigouvian fines (2)	Pigouvian fines scaled by 1/3 (3)	Pigouvian fines scaled to yield base pollution damages (4)
Compliance (percent)	95.11 (0.22)	96.69 (1.05)	95.38 (1.78)	82.44 (4.60)
Regular violator (percent)	3.47 (0.25)	1.60 (0.30)	2.09 (0.30)	2.88 (0.37)
HPV (percent)	1.42 (0.05)	1.72 (1.02)	2.52 (1.80)	14.68 (4.89)
Investment rate (percent)	0.54 (0.05)	0.86 (0.05)	0.79 (0.06)	0.53 (0.06)
Inspection rate (percent)	9.41 (0.06)	9.34 (0.33)	9.60 (0.58)	14.18 (1.72)
Fines (thousands $)	0.32 (0.03)	55.24 (1.81)	19.06 (0.69)	1.58 (1.67)
Violations (percent)	0.54 (0.01)	0.52 (0.12)	0.60 (0.21)	2.31 (0.60)
Plant utility	0.006 (0.034)	−0.349 (0.047)	−0.117 (0.038)	0.032 (0.042)
Pollution damages (millions $)	1.53 (0.03)	1.32 (0.02)	1.32 (0.02)	1.53 (0.03)

Notes: Each statistic is the long-run equilibrium mean, weighting by the number of plants by region, industry, and gravity state in our data. Plant utility reports the average flow utility across types and states including ε except for Euler's constant. Column 1 presents the results of our model given the estimated coefficients and the existing regulatory actions and outcomes. Other columns change the state-contingent fines faced by plants. All values are per plant/quarter. Bootstrapped standard errors are in parentheses.

Table 6—Counterfactual Results: by Industry

	Baseline (1)	All violators same fines; fines constant (2)	All violators same fines; pollution damages constant (3)	Pigouvian fines scaled by 1/3 (4)	Pigouvian fines scaled for base pollution damages (5)
Mining & extraction (NAICS 21)					
Fines (thousands $)	0.17	0.17	2.03	6.10	0.69
Pollution damages (millions $)	0.58	2.34	0.58	0.53	0.62
Regular violator (percent)	4.86	3.71	3.58	3.36	4.16
HPV (percent)	0.76	26.23	1.16	1.93	13.81
Utilities (NAICS 22)					
Fines (thousands $)	0.88	0.88	3.38	260.83	5.82
Pollution damages (millions $)	18.78	41.69	18.78	15.81	16.00
Regular violator (percent)	4.11	2.82	3.43	1.68	2.54
HPV (percent)	3.93	35.31	5.89	3.51	7.41
Manufacturing: metal (NAICS 33)					
Fines (thousands $)	0.25	0.25	1.51	5.10	1.39
Pollution damages (millions $)	0.40	1.50	0.40	0.33	0.55
Regular violator (percent)	2.58	1.83	2.18	1.50	2.13
HPV (percent)	1.48	31.95	2.87	2.64	15.55

Notes: Each statistic is the long-run equilibrium mean, weighting by the number of plants by region, industry, and gravity state in our data. All columns use the GMM random coefficient estimates. Column 1 presents the results of our model given the estimated coefficients and the existing regulatory actions and outcomes. Other columns change the plants' fines and cost of HPV status. All values are per plant/quarter.

removes escalation, holding fines constant—the increase in HPV status relative to the baseline varies across industries. While the fraction of plants in HPV status increases by a factor of 8 for utilities, it increases more than 20 times for the other two industries. This suggests that there are substantial differences across industries in the gains from dynamic enforcement. Column 3 shows that the increase in fines that is required to hold pollution damages constant without dynamic enforcement also varies substantially across industries. For utilities, average fines only increase by 284 percent, whereas for mining and extraction, they increased by nearly 11 times their original level (1,094 percent).

Columns 4 and 5 make clear the benefits of Pigouvian fines: since utilities have substantially higher pollution damages than any other industry, their fines also increase more. Column 5 shows that, when holding pollution damages the same as the baseline, scaled Pigouvian fines reallocate pollution damages from utilities to other industries with lower marginal pollution damages. However, this column also highlights the cost of Pigouvian fines: the fine level required to achieve the same total amount of pollution damages is substantially higher than with dynamic enforcement, and this burden falls particularly on utilities,where fines increase by 561 percent. We take this as suggestive that the EPA finds imposing fines on utilities that are commensurate with their pollution damage levels to be relatively costly.

V. Conclusion

This paper measures the value of dynamic enforcement in the context of the Clean Air Act Amendments. We build and estimate a dynamic model of a plant which is faced with a regulator and must choose when to invest in pollution abatement. We estimate a nonparametric random coefficients specification that is computationally tractable and that allows for wide heterogeneity in plants' costs from regulatory scrutiny.

We find that there are substantial and heterogeneous costs to plants of investing in pollution abatement and of facing regulator enforcement actions, particularly fines and designation as a high priority violator. For 95.7 percent of plants, the mean investment costs are equivalent to between \$218,000 and \$450,000 in fine costs and the relative heterogeneity in plants' regulatory compliance cost is even larger.

Our counterfactuals yield three main takeaways. First, we find that dynamic enforcement is valuable when fines are costly to the regulator: removing dynamic enforcement would increase pollution damages by 164 percent if fines were held constant or raise fines by 519 percent if pollution damages were held constant. These high benefits derive in part from the heterogeneous plant types (and an inability to contract on type). Second, increasing the extent to which fines escalate with the regulatory state would add little additional value: a doubling of fines for plants in HPV status would increase assessed fines by 13 percent but only lower pollution damages by 3.3 percent. Third, while scaled Pigouvian fines optimally reallocate enforcement to sectors with high marginal pollution damages—specifically utilities—they do not exploit marginal deterrence. Pigouvian fines scaled to have the same level of pollution damages as in the baseline lead to more plants in HPV status and fewer in regular violator status, which further leads to a 394 percent increase in assessed fines. Our Pigouvian counterfactuals demonstrate empirically the theoretical point that dynamic enforcement can add value by underdeterring first-time violators relative to repeat offenders, in order to increase marginal deterrence.

While we believe that this analysis provides substantial evidence that dynamic enforcement is valuable, our approach is limited in certain ways. First, we lack detailed pollution data for the majority of observations in our data and can only use more aggregate pollution information. Relatedly, our measure of plant investment in regulatory compliance is imprecise in that it is derived from regulator responses and generally does not include smaller process improvements that may improve plant regulatory compliance. In addition, identification of our model relies on a series of assumptions, including that plants' perceptions of regulatory actions match our regulatory conditional choice probabilities. Finally, by modeling the regulator using conditional choice probabilities, we give up the ability to vary inspection policies and regulatory state transition functions in our counterfactuals. Future research could extend our approach by modeling regulator decisions.

Overall, this analysis provides the first empirical estimates of the plants' responses to the dynamic environmental regulations used around the world. Our modeling framework and results on dynamic enforcement for the CAAA may allow for the evaluation of dynamic enforcement in a variety of other settings.

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