Recidivism, Enforcement, and Environmental Compliance

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Abstract

In this paper, we consider environmental recidivism. We demonstrate that regulators treat repeat offenders significantly more harshly than non-repeat offenders. This harsher treatment of repeat offenders persists; once a facility is treated as a repeat offender, it is treated as a repeat offender for many years. These findings are highly consistent with dynamic information gathering game theories but less consistent with static law and economics models and well cited enforcement leverage games. We also demonstrate that fines directed towards non-repeat offenders deter more violations, on average, than fines directed towards repeat offenders. Consequently, the current harsh treatment of repeat offenders may be an inefficient use of limited enforcement resources.

1. Introduction

Regulatory punishment for violations is a mainstay of nearly every industrialized nation's pollution policy. However, the effectiveness and efficiency of environmental enforcement is increasingly criticized. A recent U.S. Office of Management and Budget (OMB) review of the nation's civil environmental enforcement program assessed performance as merely 'adequate.' The new Environmental Protection Agency (EPA) administrator, Lisa Jackson, stated publicly that "the time is long overdue for EPA to reexamine its approach" to enforcement. Both OMB's and Administrator Jackson's action plan for improved performance emphasized an increased focus on recidivism, repeat offenses, and chronic noncompliance.[1] This paper takes up these issues.

Relapse into illegal behavior is not just a significant practical issue; recidivism is a prominent scholarly topic as well. A large legal literature examines the pervasive characteristics and societal treatment of repeat offenders. Contexts include drunk driving, labor regulations, violent crime, tax evasion, medical malpractice, and environmental compliance. A sizeable and increasingly controversial theoretical economics literature also considers the optimal treatment of repeat offenders. The standard law and economics textbook model indicates that optimal penalties should be unrelated to past offense history. Other models predict optimal penalties that decline in the number of past offenses. Recent dynamic models often suggest that repeat offenders should be sanctioned more severely than non-repeat offenders. This latter category contains two enforcement models that are especially relevant to the environmental context:

[1] OMB, "Program Assessment Rating Tool (PART) Review of EPA Enforcement of Environmental Laws (Civil)." 2005; Lisa Jackson, "Testimony before the U.S.House of Representatives Committee on Transportation and Infrastructure." Oct. 15, 2009.

information gathering games (e.g. Chu et al. 2000) and leverage games (e.g. Landsberger and Meilijson 1982; Harrington 1988).

Despite the attention that recidivism receives in the policy community, legal scholarship, and the economic theory literature, we know very little about the empirics of repeat offenses and chronic noncompliance. We know especially little about environmental recidivism, and even the basic stylized facts are largely unknown. Under major environmental statutes like the Clean Air Act, the Clean Water Act, and the Superfund Act, repeat offenders may be subject to double or treble penalties. However, environmental enforcement is typically administered at the regional, state, and local level, and statutory guidelines are not followed strictly. Incomplete enforcement is the norm, and observed regulatory activities vary significantly across both space and time (Harrington 1988; Russell 1990; Shimshack and Ward 2005, 2008). Public agencies have limited budgets, respond to local economic conditions (Deily and Gray 1991), and may be sensitive to regulatory capture (Peltzman 1976, Sunstein 1992).

In this paper, we first examine how environmental authorities treat repeat offenders relative to non-repeat offenders. We then investigate which theoretical economic motivations are most consistent with the observed pattern of regulator behavior. The goal for these first two research investigations is primarily descriptive; we wish to establish the empirical facts of recidivism in an environmental context and understand any implications for related economic theories.

We next turn to the more nuanced issue of differential enforcement deterrence across recidivist classes. Conventional policy wisdom holds that targeting the majority of enforcement resources towards repeat offenders and chronic non-compliers is the most effective way to enhance overall environmental performance. Indeed, this appears to be a central component of current federal agency action plans for improving environmental enforcement. However, this wisdom may be incorrect in practice. Recidivists may have high compliance costs and may therefore be less apt to respond to penalties as strongly as non-recidivists. Further, sanctions consistently directed towards the worst violators may signal a "free pass" to relatively better performers.

We explore all of our research questions using a novel panel of plant-level water pollution violation and sanction data from the EPA's Permit Compliance System. Our sample includes nearly every major manufacturing facility continuously operating under Clean Water Act regulations between 1996 and 2006. In contrast to much of the related literature, our compliance data covers significant violations for every regulated water pollutant.

We find three key empirical facts. First, monetary sanctions are infrequent and typically small relative to penalties allowable under the law. Second, regulators treat repeat offenders significantly more harshly than non-repeat offenders; a violation by a repeat offender is much more likely to trigger a penalty than a similar offense by a non-repeat offender. The penalty will also be much larger on average. Third, the harsher treatment of repeat offenders persists; once a facility is treated as a repeat offender, it is treated as a repeat offender for many years.

These three empirical findings are not consistent with static law and economic models of enforcement. Offense history strongly influences subsequent regulator behavior. Our empirical facts, however, are consistent with dynamic information gathering games. Interestingly, the evidence is considerably less consistent with the dynamic leverage games that are economists' most frequently cited models of environmental enforcement.

Our deterrence explorations reveal that fines directed towards non-repeat offenders deter more violations, in both an absolute and relative sense, than fines directed towards repeat offenders. *(Highly)* Preliminary simulations suggest that the reallocating the marginal fine from a repeat offender's violation to a non-repeat offender's violation may increase the statewide deterrence impact by as much as two times. Implications for regulatory targeting follow; the current harsh treatment of repeat offenders may be an inefficient use of limited enforcement resources. Policy proposals for even more attention to this relatively small group may lead to even greater inefficiencies.

2. Context

2.1 Background

Water pollution and compliance from U.S. manufacturing facilities are the focus of our analysis. Permitting, inspection, and enforcement activities are typically conducted by state-level regulatory authorities under the auspices of the National Pollution Discharge Elimination System (NPDES). Monthly self-monitoring reports are the primary source of compliance information. On-site regulator inspections are intended to ensure the accuracy of these self-reports.

Enforcement actions range from levying fines to making warning telephone calls. The full deterrent effect of fines may be greater than the nominal monetary cost, which is often significant by itself. Fines may be signals of a broad willingness to be tough on non-compliance, and increased regulatory threats may include more severe penalties in the future.

Plants may avoid violations through pollution abatement. Historically, most abatement under the NPDES program was from external end-of-pipe treatment. More recently, external treatment options have been increasingly coupled with modern production practices that mitigate water pollution discharges. With either abatement approach, discharges may be volatile from the plant's perspective. For example, efficiency of common treatments, including screening, sedimentation, and biological processes, is sensitive to temperature, acidity, light, other climatic conditions, chemical concentrations, nutrient concentrations, and microorganism concentrations.

2.2 Literature

2.2.1 The Law and Economics of Recidivism

We contribute to the law and economics literature on recidivism by comparing common theoretical predictions to empirical evidence in an environmental context. Key models include the static first-best model, a dynamic information gathering model, and a dynamic enforcement leverage model. Other important theories exist in the literature (e.g. Emons 2003, Emons 2004, and Miceli and Bucci 2005), but these models rely on assumptions unlikely to hold in an environmental context.[2]

In the standard static law and economics textbook model of offense history, the key prediction is that compliance history has no bearing on the expected penalty for a violation. Optimal penalties are purely a function of marginal social damages, and harm from the marginal violation is unrelated to offense history. This first-best model relies on assumptions of deterministic compliance, zero enforcement costs, full information, and unlimited penalties. These assumptions may be unlikely to hold for most environmental

[2] Assumptions include conditions like high exit costs from incarceration.

contexts, where discharges are stochastic, enforcement is costly, and penalties are restricted by legal mandates and political realities.

Information gathering models focus on the consequences of imperfect information in the presence of non-zero enforcement costs. The information gathering theme dates back at least to Stigler (1970), who noted "that the first-time offender may have committed the offense almost accidentally and with negligible probability of repetition, so heavy punishments (which have substantial costs to the state) are unnecessary." Works which formally develop models in this area include Rubinstein (1979) and Chu, Hu, and Huang (2000). While the most obvious costs to the state of a sanction involve imprisonment for criminal activity, civil sanctions in environmental cases often involve high costs as well. Administrative legal costs are a direct example. Malik (1990) develops a model where offenders engage in socially costly activities to avoid sanction and demonstrates that sanctions should often be less than the maximum possible in these circumstances. Such avoidance activities might include extensive litigation, concealing offenses, or even lobbying politicians to loosen regulations.

Information gathering models are associated with three key predictions. First, fines are infrequent and most fines will be modest in size. Enforcement is costly, and quasi-accidental violators are unlikely to violate again in the near future even if they face small or even no penalties. Second, sanctions increase with offense history. Repeated violations signal that the repeat offender has high costs of compliance, and high sanctions are required to induce compliance. Third, once a facility becomes characterized as a repeat offender, higher sanctions for future violations are persistent in the medium to long run. The intuition here is that since compliance costs do not typically change quickly, the high penalties necessary to deter violations will not change quickly.

Enforcement leverage games focus on the consequences of legally limited penalties. Two influential papers on this theme are Landsberger and Meilijson (1982) and Harrington (1988). Harrington (1988) is one of the more cited studies in both law and economics and environmental economics. In the Markovian state-dependent enforcement models underlying leverage games, the maximum penalty is assumed to be insufficiently high to achieve continuous compliance. However, the regulator can obtain partial compliance by arranging a scheme which allows some violations with low (or zero) penalties if the firm complies at prescribed times. Implicitly the total penalty for violating at the prescribed times includes not only the immediate fine, but also fines for the violations which would otherwise have been unpunished. In short, in leverage models, plants which comply at the prescribed times enjoy a reduced expected sanction in subsequent periods compared to the repeat offenders. Polinsky and Shavell (1998) develop a similar two-period model under the assumption of limited penalty with similar results: compliance in an initial period is obtained by treating repeat offenders more harshly in the second period.

The essence of agency behavior in leverage models is associated with three key predictions.[3] First, fines are infrequent but are large when levied. The regulator achieves some compliance by coupling a 'free pass' for occasional violations (a reward for reasonably good behavior) with a serious threat for more frequent violations (an especially severe penalty for bad behavior). So observed penalties, when levied, should

[3] We do not test predictions from a literal interpretation of leverage models since they have few testable implications as written, as the Harrington (1988) study itself notes. Literal interpretations also predict degenerate and unrealistic cases like no fines in equilibrium.

be large. Second, sanctions increase with offense history. At least in the short run, repeat offenders have forsaken their reward for good behavior and violations will be sanctioned. Third, a facility's characterization as a repeat offender should be relatively short-lived. Even frequent violators should observe alternating periods of high sanctions and limited enforcement. The intuition is that the regulator forgoes the leverage necessary to ensure *any* compliance if it doesn't allow plants back into the 'good behavior' category.

2.2.2 Environmental Enforcement

We also contribute to the empirical economics literature on environmental enforcement. This literature emphasizes the direct role of coercive enforcement in reducing violations and pollution. Studies by Magat and Viscusi (1990), Laplante and Rilstone (1996), Earnhart (2004a, 2004b), and Shimshack and Ward (2005, 2008) investigated the impact of inspections, the threat of inspections, and fines on water pollution compliance rates and discharges. Gray and Deily (1996), Nadeau (1997), Gray and Shadbegian (2005, 2007), and Keohane et al. (2009) explored the impact of enforcement actions and the threat of enforcement actions on compliance rates, the duration of noncompliance, and emissions in an air pollution context. Stafford (2002) showed that an increase in the maximum possible penalty decreased violations for hazardous waste polluters. The above papers represent important contributions to the empirical enforcement literature. However, none of those papers highlight offense history and its relationships to regulator behavior, plant behavior, or enforcement deterrence.

3. Data

3.1 The Permit Compliance System and a Comprehensive Pollution Measure

We investigate the empirics of environmental recidivism using the EPA's Permit Compliance System (PCS). Established in conjunction with the Clean Water Act and its amendments, the PCS tracks monthly plant-level self-reported discharges, permitted effluent limitations, inspections, and enforcement actions.

Our sample facilities include 'major' manufacturing sources. The EPA identifies plants as major if they have a flow of one million gallons or more per day or pose a significant impact to water quality. We only consider major plants because these facilities are required to report their own discharges levels for operating pipes each month. Industries with commonly regulated major manufacturing facilities include organic chemicals, inorganic chemicals, plastic materials, paper mills, pulp mills, paperboard mills, and iron and steel works.

Our final sample of plants includes 1102 major manufacturing facilities in 34 states. From the universe of 1210 major manufacturing plants regulated under the Clean Water Act, we selected all facilities operating in states with 6 or more major manufacturers. The spillover effects of regulation on other plants will be important to our facility-level analysis, so we only consider plants in states with at least a modest number of facilities. Our only other criterion was completeness; we kept all plants that were officially designated by EPA as "active" for entire 1996 to 2006 sample period.

Our total sample period covers the 125 months spanning January of 1996 to May of 2006. Our compliance sample, chosen for data availability reasons, covers the 65 month subset spanning January of 2001 to May of 2006. The PCS began a phase out in June of 2006; compliance data from that month forward are incomplete and unreliable. Credible compliance information in the public version of the PCS also spans less than 6 years, so 2001 is the earliest year with dependable data. Once we defined the compliance sample, we collected enforcement data covering the sample period plus a full five years of lags.

Our dataset contains full information on administrative fines and water pollution compliance for major manufacturing facilities. Fines are monetary charges typically imposed by the state or regional administrative authority, rather than a court, for a violation. Our compliance metrics are EPA-designated significant non-compliance (SNC) eligible effluent violations. These are defined as serious violations under the Clean Water Act, although the precise determination is complex. In brief, for major facilities, SNC-eligible monthly average violations must be greater than 40% above monthly average limits for certain conventional pollutants (like biochemical oxygen demand and suspended solids) and greater than 20% above monthly average limits for certain toxic and non-conventional pollutants.[4] An advantage of the SNC designation is that it simultaneously summarizes a plant's water pollution compliance across all pollutants and discharge points. In other words, our dataset simultaneously captures violation information for *every* regulated water pollutant from *every* discharge point for nearly every major manufacturer facility in the United States.

The majority of the underlying violation data that triggers officially designated SNC in the PCS, and thus in our empirical analysis, is self-reported. Intentional misreporting is punishable by large criminal sanctions, including jail time. These criminal penalties are borne directly by employees, unlike the sanctions for effluent violations that we study. Consequently, there are strong incentives for truthful reporting. Further, a USEPA Center for Environmental Information and Statistics (1999) independent analysis has verified the accuracy of PCS data.

[4] For more information, see the EPA description at http://www.epa-echo.gov/echo/index.html.

4. Summary Statistics and Statistical Relationships

In this section, we summarize some empirical facts related to environmental recidivism in a water pollution context. We first present basic summary statistics on violations and fines. Our primary goal here is to more completely understand the context. We next explore the regulatory response to repeat offenders relative to the regulatory response to non-repeat offenders. First, we examine if the likelihood and magnitude of fines differ for repeat offenders and non-repeat offenders. Second, we examine if observed differences persist.

4.1 Violation Summary Statistics

In an average month, approximately 2.8 percent of plants had a significant non-compliance (SNC) eligible effluent violation. In total, there were 2,015 significant effluent violations out of the 71,630 possible compliance observations covering 1102 plants over 65 months. Violation rates trended somewhat downward over our sample period, although non-linearly. The lowest rate was 2.6 percent in 2006 and the highest rate was 3.1 percent in 2001. Violations varied significantly across space. Mean state-level violation rates ranged from 0 in Delaware and Virginia to over 8.4 percent in West Virginia.

We find evidence for significant differences across plants in the propensity to violate. 793 plants (72 percent of facilities) did not have a significant effluent violation over the 65 month sample period. 309 plants (28 percent of facilities) violated one or more times. 130 plants (12 percent of facilities) violated 5 or more times and 61 plants (5 percent of facilities) violated ten or more times. The most frequent violator had a significant effluent violation in 61 of 65 possible months.

4.2 Fine Summary Statistics

Table 1 presents descriptive statistics for administrative fines. Recall that the sample period for fines is approximately twice as long as the compliance sample period. There were 459 fines levied against 215 facilities over the 125 month sample enforcement period. 98 of the fined facilities received more than 1 fine, and the most frequently fined plant received 18 fines over the period spanning January 1996 to May 2006. The mean fine was approximately $45,000, but the median fine was only $5000. Note that fine magnitudes should be interpreted relative to the gain in plant-level profits obtained by exceeding a given pollution standard in a given month, not relative to the overall operating revenue of a plant.

Table 1. Fine Summary Statistics: Jan. 1996-May 2006

Total Fines	States Levying Fines	Median Fine	Mean Fine
459	27	$5000	$45,384

Fine numbers declined modestly over time; there were approximately 50 fines annually between 1997 and 2003 and approximately 30 fines annually between 2004 and 2006. Fines were also not distributed evenly across space, as both the number and magnitude of fines (even when scaled by plants) varied significantly across states. Seven states levied no administrative fines on sample plants over the sample period.

We highlight two key facts about enforcement actions before proceeding. First, monetary penalties are rare relative to the number of violations. Second, monetary penalties tend to be modest relative to those allowable under the law. The Clean Water Act permits penalties as high as $50,000 per day of violation. Our sample median fine for significant effluent violations from the country's largest manufacturers was $5000, and many of these fines addressed violations that lasted one or more months.

4.3 Regulatory Treatment of Repeat Offenders

In this section, we explore statistical relationships between repeat offender classifications and regulator behavior. For a first pass, we assume that all significant non-compliance (SNC) violations are of equal magnitude (Modifiable Assumption #1). We compare the relationship between additional violations and the probability and magnitudes of sanction for repeat offenders versus non-repeat offenders.

Since the relationship between violations and sanctions may be confounded by regulator characteristics, common shocks, and plant characteristics beyond recidivism, we explore our basic relationships in a plant-level regression context. Quarterly dummies control for variations in production, regulator behavior, and pollution limits due to seasonality. Annual dummies control for technical change, political conditions, and economic factors common across all states. State-specific time trends account for trends in political and economic factors within a state. Plant-level fixed effects control for industry, industrial subcategory, size, managerial attitudes, and other quasi-fixed facility characteristics.

Our dependent variables is these descriptive regressions are (1) the existence of a fine levied at plant i in period t and (2) the logged magnitude of {fines+1} levied at plant i in period t.[5] The key explanatory variables are the number of unfined significant effluent violations at plant i in the 2 years (1-24 months) preceding period t interacted

[5] We add 1 to fine magnitudes before taking logs to prevent undefined quantities for periods with no fines.

with indicator variables for repeat offender and non-repeat offender.[6] All regressions are linear, so fine regressions with limited dependent variables can be thought of as linear probability models (Modifiable Assumption #2).[7]

We initially define a repeat offender by fine history rather than violation history (Modifiable Assumption #3). We choose this approach since many violations are unsanctioned, and many violations may be interpreted as unintentional given stochastic discharges. Thus, violations may not signal that a plant is considered by the regulator to be a prior and persistent 'bad apple.' Fines, however, likely do signal such a designation, at least in the short run. For a first pass, recidivists are defined as plants with a fine in the past five years, a fine in the past two years, and a fine 3 or 4 years ago (Modifiable Assumption #4).

Table 2 presents results for regressions exploring how the probability of a fine for the marginal violation differs between repeat offenders and non-repeat offenders. Robust standard errors, clustered at the plant-level, appear in parentheses below the key coefficient estimates. We cluster errors to allow for arbitrary serial correlation at the plant-level. Results in row 1 indicate that the probability of a fine for a non-repeat offender increases by about .001 (about one-third of the baseline probability) for each additional unfined violation in the previous two years. Results in row 2 suggest that the probability of a fine for a repeat offender increases by about .003 - .004 for each additional unfined violation in the previous two years. In short, an additional unfined violation by a repeat offender is 3-4 times more likely to result in a fine than an additional unfined violation by a non-repeat offender. Violations by a repeat offender are

[6] Results are robust to lagged unfined violations broken up into separate one and two year lags, as well as alternative definitions.
[7] Reassuringly, our LP models yield no negative or otherwise implausible predicted fine probabilities.

significantly more likely to trigger a penalty than similar violations by a non-repeat offender.

Table 2. Does the probability of the fine for the marginal violation differ between repeat offenders and non-repeat offenders?

Variable Description	DEPVAR: Fine Probability. RECIDIVIST: Fine in last 5 years	DEPVAR: Fine Probability. RECIDIVIST: Fine in last 1 or 2 years	DEPVAR: Fine Probability. RECIDIVIST: Fine in last 3 or 4 years
# of unfined violations in the past 2 years	0.00097**	0.00102**	0.00102**
× plant is not a repeat offender	(0.00022)	(0.00023)	(0.00024)
# of unfined violations in the past 2 years	0.00323**	0.00441**	0.00335**
× plant is repeat offender	(0.00118)	(0.00208)	(0.00174)
Seasonality Dummies	3 Season Vars.	3 Season Vars.	3 Season Vars.
Year Dummies	5 Year Vars.	5 Year Vars.	5 Year Vars.
Fixed Effects	1101 Plant FE's	1101 Plant FE's	1101 Plant FE's
State Specific Linear Time Trends (TT's)	34 State TT's	34 State TT's	34 State TT's
F Statistic, Prob > F	1.37	1.39	1.33
Prob > F	0.05	0.05	0.07

NOTES: Robust standard errors, clustered at the plant level, are in parentheses. Superscript ** indicates significance at the 5% level. All regressions have 71630 observations on 1102 firms for 65 months.

Column 2 of Table 2 presents penalty probability results for recently defined recidivists, ie. plants that have been fined 1-24 months ago. Column 3 of Table 2 presents penalty probability results for plants categorized as recidivists in the more distant past, ie. plants that have been fined 25-48 months ago. The key thing to note is that the results in row 2 are of relatively similar magnitude across columns 2 and 3. They are also statistical indistinguishable from one another. This suggests that repeat offender classification does not seem to decay quickly. Once the regulator learns that a plant is a repeat offender, it increases penalties and keeps them high for several years.

Table 3 presents results for regressions exploring how the magnitude of a fine for the marginal violation differs between repeat offenders and non-repeat offenders. Robust standard errors, clustered at the plant-level, appear in parentheses below the key coefficient estimates. Results in row 1 suggest that the logged magnitude of a fine for a non-repeat offender increases by about .009 - .010 (about one-third of the baseline probability) for each additional unfined violation in the previous two years. Results in row 2 suggest that the logged magnitude of a fine for a repeat offender increases by about .03 - .04 for each additional unfined violation in the previous two years. In short, an additional unfined violation by a repeat offender results in a proportional increase in expected penalties that is 3-4 times larger than the proportional increase for a similar violation by a non-repeat offender. Violations by a repeat offender trigger significantly larger expected penalty increases than similar violations by a non-repeat offender.

Table 3. Does the size of the fine for the marginal violation differ between repeat offenders and non-repeat offenders?

Variable Description	**DEPVAR: Log Fine Amount. RECIDIVIST: Fine in last 5 yrs**	**DEPVAR: Log Fine Amount. RECIDIVIST: Fine in last 1 or 2 years**	**DEPVAR: Log Fine Amount. RECIDIVIST: Fine in last 3 or 4 years**
# of unfined violations in the past 2 years	0.00931**	0.00985**	0.00981**
× plant is not a repeat offender	(0.00215)	(0.00226)	(0.00233)
# of unfined violations in the past 2 years	0.03216**	0.04261**	0.03340**
× plant is repeat offender	(0.01159)	(0.01987)	(0.01720)
Seasonality Dummies	3 Season Vars.	3 Season Vars.	3 Season Vars.
Year Dummies	5 Year Vars.	5 Year Vars.	5 Year Vars.
Fixed Effects	1101 Plant FE’s	1101 Plant FE’s	1101 Plant FE’s
State Specific Linear Time Trends (TT’s)	34 State TT’s	34 State TT’s	34 State TT’s
F Statistic, Prob > F	1.28	1.30	1.24
Prob > F	0.10	0.09	0.14

NOTES: Robust standard errors, clustered at the plant level, are in parentheses. Superscript ** indicates significance at the 5% level. All regressions have 71630 observations on 1102 firms for 65 months.

Column 2 of Table 3 presents penalty magnitude results for recently defined recidivists, ie. plants that have been fined 1-24 months ago. Column 3 of Table 3 presents penalty magnitude results for plants categorized as recidivists in the more distant past, ie. plants that have been fined 25-48 months ago. The key thing to note is that the results in row 2 are once again of relatively similar magnitude across columns 2 and 3. They are still statistical indistinguishable from one another. This suggests again that repeat offender classification does not seem to decay quickly. Once the regulator learns that a plant is a repeat offender, it increases penalties and keeps them high for several years.

5. Recidivism and Enforcement Deterrence

In this section, we use panel-data techniques to analyze plants' discharge responses to changes in regulatory enforcement directed towards repeat offenders and non-repeat offenders. Our primary goal is to understand how deterrence differs between the marginal fine levied against a repeat offender and the marginal fine levied against a non-repeat offender.

5.1 Motivating an Empirical Model for Plant Behavior

We take the standard view of the regulated plant as a rational decision-maker that undertakes abatement effort to the point where the expected marginal cost of such effort equals the corresponding expected marginal benefit (Becker 1968, Stigler 1970). Plant characteristics, like industry, size, and management, influence plants' expected marginal benefits and marginal costs of abatement. Since production and discharge limits may vary quarterly, seasonality influences plants' expected marginal benefits and marginal costs as well. Technological change, changing political factors, and national or state economic shocks may also influence marginal benefits and marginal costs. Thus, plants' compliance decisions are a function of facility characteristics, seasonality, national shocks, and state-specific shocks.

A critical determinant of a plant's expected marginal benefit from abatement is the avoided penalty for a violation. With self-reported pollution discharges and relatively frequent monitoring, we assume perfect compliance detection (Modifiable Assumption #5). We also assume that fine magnitudes are fixed (Modifiable Assumption #6). The key driver of a plant's expected sanction in our simple model, then, is the expected probability of a fine for a violation.

A plant's decision to comply is a function of its beliefs about the probability of a sanction for a violation given its current recidivist classification. Since current compliance behavior can influence its recidivist classification and its expected penalties in the future, a plant's decision to comply may also be a function of its beliefs about expected sanctions if it moves to a different recidivist classification. In other words, a plant's compliance decision is a function of expected sanctions for both recidivists and non-recidivists. Although the plant can only designated as a 'good guy' or a 'bad guy' today, its current decisions may depend on the consequences of possibly switching groups in the future.

Operationalizing plant *i*'s compliance problem in period *t* motivates a basic model of the form:

$$y_{it} = f(\alpha_i, X_{it}, ES_{Bit}, ES_{Git}; B), \qquad (1)$$

where α_i is a plant-specific fixed effect, ES_{Bit} represents plant i's expected belief of the probability of a sanction for a violation when i is a recidivist (a 'bad guy'), ES_{Git} represents plant i's expected belief of the probability of a sanction for a violation when i is a non-recidivist (a 'good guy'), and X represents a vector of controls for seasonality, common time variant shocks, and state-specific time variant shocks. B is an indicator for recidivist class.

Plant beliefs are unobservable to the researcher. Our best guess of how plants form beliefs about the likelihood of a sanction given a violation is a prediction similar in spirit to our own predictions in Table 2. In other words, we assume plants form perceptions about regulator behavior based upon observing average relationships between violations and sanction probabilities. Expected regulatory behavior differs by recidivist classification, so we assume plants may form different expectations for each recidivist class.

While we assume that plants base perceptions on average relationships between compliance outcomes and regulator behavior over time, we also assume that plants may be uncertain about predicted regulator behavior at any given point in time. State and regional politics, budgets, priorities, and personnel change over time, so plants' assessments of the regulatory threats may change over time as well. Following Sah's [25] work on social osmosis in crime, we assume that facilities regularly update their beliefs based upon experience. An important credible source of information about the probability of a fine is the enforcement history of the regulator. The most informative data about current conditions is from the recent past; recent sanctions by a regulator, on any plant, affect the regulator's overall credibility and thus impact each plant's perceived threat of a fine. This reputation-induced spillover effect of enforcement actions on the behavior of non-sanctioned facilities is known in the law and policy literature as *general deterrence*. Previous empirical work demonstrates that general deterrence can be much larger than plant-specific deterrence effects since it applies to many facilities rather than to one facility (Shimshack and Ward 2005).

We therefore augment plants' prediction models with instruments based upon the number of fines on another plant j in plant i's state in any of the 12 months prior to t. We omit plant i itself from the instrument to avoid introducing endogeneity from serial correlation in plant-specific shocks. Operationalizing plant i's reduced form prediction equations for regulator behavior yield relationships of the form:

$$ES_{Git} = g(\alpha_{Gi}, X_{Git}, V_{Git}, Z_{Git}) \tag{2a}$$

$$ES_{Bit} = g(\alpha_{Bi}, X_{Bit}, V_{Bit}, Z_{Bit}), \tag{2b}$$

where V_{it} represents violations in the recent past and Z_{it} represents (lagged) fines levied against other plants in the same state and sector in the previous year.

Plugging equations (2a) and (2b) into (1) yields a reduced form equation for plant-level compliance decisions of the form:

$$y_{it} = h(\alpha_i, X_{it}, V_{it}, Z_{it}; B). \tag{3}$$

Our primary goal is to understand how the general deterrence effects of fines levied against repeat offenders differ from the general deterrence effects of fines levied against non-repeat offenders, so we are directly interested in the reduced form (3).

5.2 Results

To implement (3), we regress the existence of a violation at plant i in period t on the number of fines on another plant j in plant i's state in any of the 12 months prior to t. More precisely, we regress our dependent variable on: (1) the number of fines on another repeat offender in plant i's state interacted with an indicator variable representing if plant i is a repeat offender, (2) the number of fines on a non-repeat offender in plant i's state interacted with an indicator variable representing if plant i is a repeat offender, (3) the number of fines on a repeat offender in plant i's state interacted with an indicator variable representing if plant i is a non-repeat offender, and (4) the number of fines on another non-repeat offender in plant i's state interacted with an indicator variable representing if plant i is a non-repeat offender. We also include several controls, including plant-level fixed effects, seasonality dummies, annual dummies, and state-specific time trends. As before, repeat offenders are defined as plants with a fine in the previous 5 years (Modifiable Assumption #7).

Table 4 presents results of plant-level regressions. Standard errors are in parentheses below coefficient estimates. Results indicate that the estimated impact of a fine on another facility in the same state on subsequent violation probabilities is typically negative and strongly significant for both repeat offenders and non-repeat offenders. In column 1, we see that average violation probability for non-repeat offenders declines 0.00194 in the year following a fine on another non-repeat offender. The average violation probability for a recidivist declines 0.00236 in the year following a fine on a non-repeat offender. Given overall mean violation rates for non-repeat offenders, the general deterrence effects to a non-repeat offender (a 'good apple') of a fine levied against similar plants (another 'good apple') translates into an approximately 7 percent reduction in violations. Given overall mean violation rates for repeat offenders, the general deterrence effect to a repeat offender (a 'bad apple') of a fine levied against a non-repeat offender (a 'good apple') translates into an approximately 7 percent reduction in violations.

Table 4. What are the general deterrence implications of regulator behavior?

Variable Description	LP Model	Conditional Fixed Effects Logit
Fine 1-12 months ago on a different repeat offender in state ×	-0.00156**	-0.17963**
plant is a repeat offender	(0.00063)	(0.04630)
Fine 1-12 months ago on a non-repeat offender in state ×	-0.00236*	-0.18890**
plant is a repeat offender	(0.00131)	(0.06384)
Fine 1-12 months ago on a repeat offender in state ×	-0.00085	-0.10956**
plant is a non-repeat offender	(0.00053)	(0.04198)
Fine 1-12 months ago on a different non-repeat offender in state ×	-0.00194**	-0.18704**
plant is a non-repeat offender	(0.00070)	(0.04578)
Violations 1-24 months ago ×	0.01624**	0.12469**
plant is a repeat offender	(0.00042)	(0.00945)
Violations 1-24 months ago ×	0.01738**	0.12822**
plant is a non-repeat offender	(0.00098)	(0.01961)
Seasonality Dummies	3 Season Vars.	3 Season Vars.
Year Dummies	5 Year Vars.	5 Year Vars.
Fixed Effects	1101 Plant FE's	308 Plant FE's
State (Regulator) Specific Linear Time Trends (TT's)	34 State TT's	34 State TT's

NOTES: Standard errors are in parentheses. Superscripts **,* indicates significance at the 5% level and the 10% level, respectively. LP regressions have 71630 observations on 1102 firms for 65 months. The conditional fixed effects logit model has 20085 observations on 309 plants for 65 months; plants with no effluent violation over the 65 month sample are dropped from the analysis.

While the impact of a given fine is generally similar for repeat offenders and non-repeat offenders, the deterrence impacts of fines levied against repeat offenders and levied against non-repeat offenders differ. For both repeat offenders and non-repeat offenders, the deterrence effects of fines directed towards 'good apples' deter more violations than fines directed towards 'bad apples.' Perhaps facilities consider the regulator to be especially aggressive when it fines 'good apples.'

5.3 General Deterrence Discussion

The general deterrence results above are subject to numerous caveats. Findings are highly preliminary and somewhat sensitive to specification. Reputation measures may be imperfect. If a given plant can observe violations at another plant, the appropriate reputation measure may be fines per violation. Also, even though our instruments are (1) lagged and (2) on facilities other than plant i, endogeneity concerns may arise. For example, enforcement is driven in large part by lagged violations. Such violations may in turn be driven by statewide economic and political conditions. If such statewide shocks are serially correlated, it is possible that enforcement at other plants in the state may be correlated with the error term in for plant i. If present, such endogeneity would bias our deterrence results positively, thereby understating the overall deterrence impacts of fines. However, the degree to which this type of bias affects the differential deterrence effects across recidivists and non-recidivists is unknown.

However, our current general deterrence results have interesting implications for regulator targeting. Most notably, we find strong evidence that recidivists are more frequently and severely punished, but we find no evidence for particularly large general deterrence effects from fines directed towards these repeat offenders. On average, we find larger general deterrence effects from fines directed towards non-repeat offenders. Fines targeted towards repeat offenders may achieve a desired specific deterrence result (which we do not explore here), but fines targeted towards non-repeat offenders may well achieve greater general deterrence. Given general deterrence impacts many facilities simultaneously, targeting enforcement towards recidivists may not achieve the largest enforcement 'bang for the buck.'

To interpret our results, we perform a simulation exercise to understand this last issue more completely. Steps proceed as: (1) We use current regression estimates to predict the expected number of violations given the current allocation of fines to recidivists and non-recidivists. (2) For an instance of an unfined 'good apple' violation and a fined 'bad apple' violation, we artificially assign the marginal fine to the 'good apple' instead of the 'bad apple.' Note that we keep the number of fines fixed, so regulator costs may be roughly similar. Once we artificially flip the fine assignment, we predict a new expected number of violations. (3) We average over all cases in step 2 and examine the differences. *(Highly)* Preliminary simulations suggest that the reallocating the marginal fine from a repeat offender's violation to a non-repeat offender's violation may increase the statewide deterrence impact by as much as two times.

Conclusion

We find infrequent and small fines relative to those allowable under the law. We also find that regulators treat repeat offenders significantly more harshly than non-repeat offenders. Violations by repeat offenders are 3-5 times more likely to receive a fine than an equivalently significant violation by a non-repeat offender. Similarly, violations by repeat offenders trigger penalty amounts that are 3-5 times greater than a similarly significant violation by a non-repeat offender. We discover that the harsher treatment of repeat offenders persists for several years. Recidivists defined as those with fines in the 1 to 2 years ago receive roughly the same treatment as recidivists defined as those with fines in 3 to 4 years ago.

Our regulator behavior results are most consistent with an information gathering game for the treatment of repeat offenders. In this model, regulators learn facilities' compliance cost types by their past behavior. Once a facility is considered a high compliance cost type, it faces higher penalties than other violators and these higher penalties persist. Our detected empirical facts are not consistent with the textbook static law and economics model of enforcement and offense history. Also, since observed penalties are often considerably below maximums allowable by law and recidivist classifications persist for long periods of time, our results may not be consistent with leverage models that rely on constrained penalties and especially harsh treatments when sanctions exist. One should be cautious, however, generalizing these results to contexts beyond major manufacturer's water pollution.

In addition to regulator behavior, we consider facility responses to regulator actions in the context of repeat offenders. First, we find that any given fine deters more subsequent violations, in both an absolute and a proportional sense, by repeat offenders than non-repeat offenders. However, we also find that the recipient of the fine influences facility responses. Fines directed towards non-repeat offenders deter more violations, on average, than fines directed towards repeat offenders. It is very possible that the particularly harsh treatment of repeat offenders observed in the first part of this paper represents an inefficient use of scarce enforcement resources. A greater regulatory 'bang for the buck' may be achieved by fining more violations by non-repeat offenders.

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