Costly sanctions and the treatment of frequent violators in regulatory settings*

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ABSTRACT

Regulators typically treat frequent violators more harshly. When does such harsh treatment maximize overall compliance? We consider the role of two factors: responsiveness to penalties and costs of sanctions. A novel insight is that maintaining a credible threat of sanction against infrequent violators is relatively cheap because that threat seldom needs to be backed up. In a Clean Water Act application, the marginal sanction deters ten times as many violations when directed at infrequent violators. On net, this is due to a sanction cost effect, not because infrequent violators are marginally more responsive to the threat of punishment.

KEY WORDS: Regulation; Repeat Offender; Enforcement; Compliance; Pollution; Fines

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1. Introduction

Regulatory enforcement entails substantial costs. Administrative law agencies spend billions of dollars on investigations, negotiations, and courts each year. Sanctions for non-compliance generate significant indirect political economic costs for regulators due to community, industry, and political pressure. Private compliance costs triggered by enforceable environmental, health, and safety laws total one half to two percent of GDP per year, or as much as $360 billion annually. Given the significant public and private costs at stake, understanding the optimal allocation of enforcement resources is a crucial issue for regulation.[1]

This paper considers an unsettled problem for regulators allocating enforcement resources: the treatment of violations committed by frequent versus infrequent violators. Popular wisdom, common notions of fairness, and retributive theories of punishment suggest that regulators should penalize frequent violators' offenses more severely. Actual practice in environmental, energy, financial, occupational, and health regulation follows this prescription closely.[2] Nevertheless, neither extant scholarship nor practice clearly illustrate how a regulator striving to achieve high compliance with costly sanctions and limited resources might actually determine the optimal balance when punishing frequent and infrequent violators. Despite casual economic and policy intuition to the contrary, it is not even clear that a resource constrained regulator seeking to minimize violations - as is typically required by law - should treat the marginal violation by a frequent violator more harshly than the marginal violation by an infrequent violator.

In this study, we document and explore two factors that influence the optimal regulatory balance when punishing frequent and infrequent violators. The first factor is the enforcement response effect. Intuitively, a regulator seeking to maximize compliance will want to direct marginal enforcement resources towards those facilities most likely to respond to sanctions. Frequent violators may or may not be more responsive, because frequency of violation may be associated with unobserved variation in the structure of compliance costs. The second factor is a

[1] Stigler (1970), McKean (1980), Cohen (1986), Polinsky & Rubinfeld (1989), and Magat & Viscusi (1990) provide early discussions of agency enforcement costs. Stigler (1971), Peltzman (1976), Hilton (1972), Joskow (1974), and Leaver (2009) discuss the political economy of regulation. Gray & Deily (1996), Helland (1998), Stafford (2002), Konisky (2007), and Grooms (2015) empirically illustrate political economic factors in contexts similar to our empirical setting. Pizer & Kopp (2008), and U.S. OMB (2016) summarize aggregate costs.

[2] Appendix A references select enforcement guidelines. Harsh treatment of frequent violators is standard practice at Commerce (NOAA fisheries), Labor (OSHA), Health and Human Services (FDA), Federal Energy Regulatory Commission (FERC), the Securities and Exchange Commission (SEC), the Environmental Protection Agency (EPA), and other agencies.

sanction cost effect. A novel insight here is that it is costlier to the regulator to maintain a given regulatory threat (i.e. a given expected penalty) for frequent violators. This is because sustaining credible enforcement threats against frequent violators requires the regulator to levy costly penalties frequently. In contrast, sustaining a given regulatory threat for infrequent violators may be relatively cheap because the regulator need not 'back up' threats with costly sanctions as often.

This paper makes three key contributions. First, we provide a novel characterization of the optimal punishment of violations by frequent and infrequent violators in a realistic regulatory setting. Our evidence illustrates how an agency seeking to minimize violations subject to limited enforcement resources might balance enforcement response and sanction costs across frequent and infrequent violators. Second, we show empirically the relative importance of factors driving optimal decisions using data from a Clean Water Act (CWA) regulatory setting. We use the data to build on a growing public enforcement of law literature empirically measuring deterrence effects of sanctions, but go beyond past scholarship by exploring deterrence across frequent and infrequent violators and by using the results to calibrate an optimality condition.[3] Third, we illustrate a generalizable framework for regulators considering the optimal punishment of frequent and infrequent violators in their own settings. Rather than assert that our stark CWA results will necessarily generalize, we build an apparatus for agencies to form their own conclusions.

We first construct a stylized model that illustrates the optimal regulatory punishment of violations across two types of heterogeneous entities: frequent violators and infrequent violators. The resulting first-order condition shows how enforcement response and sanction cost considerations influence the marginal benefits and marginal opportunity costs of incremental enforcement resources. We use CWA data to calibrate this condition. We focus on water quality because water pollution remains a serious issue in the United States, detected violations by frequent CWA violators are punished severely as a matter of law and practice, and CWA data are observed at high frequencies at the facility-level.[4] Our calibration exercise involves identifying three parameters empirically. Under plausible conditions, two of these parameters can be identified directly from moments of our data. We estimate the third, enforcement response, by econometrically exploring regulated facilities' responses to variation in a proxy for expected

[3] Earlier studies empirically measuring deterrence in regulatory or closely related settings are summarized in, for example, Cohen (1998), Gray and Shimshack (2011), Alm (2012), and Leeth (2012). Muehlenbachs et al. (2016) provide a recent example.
[4] See, for example, Polinsky & Shavell (1998) and Shimshack & Ward (2005).

penalties. Since the proxy may induce error-in-variables issues and expected penalties might be endogenous, we use a straight-forward application of a split-sample (two-sample) instrumental variable approach for identification. The source of variation in our empirical model is idiosyncratic changes in enforcement intensity plausibly unrelated to the behavior of the facility itself.

Our main empirical finding is that the ratio of marginal costs to marginal benefits (the 'buck per bang') is more than *ten* times higher for a marginal increase in expected penalty directed towards frequent CWA violators than for infrequent violators. Three implications follow. First, directing marginal enforcement resources towards deterring violations by infrequent violators would improve the regulatory efficiency of maximizing compliance. CWA authorities currently punish violations by frequent violators far more severely than equivalent violations by infrequent violators; on the margin, this is counterproductive if the goal is to maximize compliance. Second, policy initiatives designed to address declining enforcement resources with an even greater focus on frequent violators may move away from optimal resource allocations. This would certainly be true in our CWA context. Third, focusing only on regulated entities' enforcement response – as in the related empirical literature – may suggest misguided policy conclusions. We find that frequent violators respond more strongly in absolute terms to marginal changes in enforcement pressure than infrequent violators. Thus, a regulator focused on enforcement response alone (i.e. the marginal benefits of punishment) may want to treat frequent violators even more harshly (in a relative sense) than present circumstances. But, this behavior ignores sanction cost effects, which in our setting swamp enforcement response effects on the margin.

Our study relates to an established literature exploring the optimal treatment of frequent violators, but our regulatory setting differs markedly and the driving forces differ. The key modeling distinction between our paper and the previous literature is sanctions that are costly to the regulator. First, the most basic law and economic models of public enforcement assume social welfare maximizing agencies, zero enforcement costs, and unconstrained penalties (Shavell 2004). In contrast, we study a second-best regulatory setting where enforcement agencies are mandated to maximize compliance and where enforcement is costly. Second, a criminal enforcement literature derives the optimal treatment of repeat offenders in the presence of personal wealth constraints and exit costs from incarceration (Emons 2003, 2007; Miceli & Bucci 2005). These and other key assumptions are not applicable to our setting. Third, an enforcement leverage literature (i.e. Landsberger & Meilijson 1982; Harrington 1988; Harford & Harrington 1991;

Polinsky & Shavell 1998; Friesen 2003) studies games between regulators and facilities when penalties are costless but legally capped. Our analysis focuses on regulatory settings where enforcement is itself costly and fines never approach statutory maximums. These conditions are common in many regulatory settings. A fourth strand of the frequent violator literature stresses differing costs of compliance revealed by compliance history (Stigler 1970; Rubinstein 1979; Polinsky & Rubinfeld 1991; Chu et al. 2000). Although we share the idea that past behavior may be informative about regulated entities' response to enforcement, the mechanisms by which this heterogeneity drives regulators' optimal choices differ. Results in the related literature are driven by risks from punishing the innocent or from over-deterrence when gains are socially acceptable. We focus on costly sanctions to the regulator and on legally realistic regulatory objectives.

2. Stylized Optimization Model

In this section, we present a simple stylized static framework to make economic and policy ideas more transparent. We begin with firms that are required to comply with some regulatory rule, such as the case of limits on discharge of pollutants. The firm can take costly actions that affect the probability of violating this rule, such as changes to production, operational procedures, or maintenance. The expected penalty from the regulator for violations is one key determinant of the amount of compliance effort, and it is the focus in this analysis.[5] We use the function $V_j(P_j)$ to indicate the average violations of firm j when faced with expected penalty P_j for a violation. To emphasize, P in our model is expected penalty and not the probability of detection.

Since we seek to understand the treatment of frequent versus infrequent violators, differences across firms in the function $V_j(P_j)$ is central. Differing types reflect heterogeneity in firms' compliance costs. We assume the violation relationship $V_j(P_j)$ is fixed and known having been revealed to the regulator through a long history of interactions. Similarly, firms understand that the expected penalty for a violation may be higher for firms with poor compliance history.

We next consider a regulator. Although the theoretical literature often uses the objective of social welfare maximization, the legal mandate of most regulatory agencies is to ensure high levels of compliance. So, we model a regulator that seeks to minimize violations across all firms given limited enforcement resources. To keep our analysis focused, and to match many regulatory

[5] Of course, other factors such as corporate social responsibility and risk of bad publicity or activist attention also play roles in compliance effort (Kitzmuller & Shimshack 2012).

settings, we consider the case where the cost to regulators of observing violations is small. One such setting is where self-reporting is incentive compatible and the primary monitoring strategy.

Levying fines, even for self-reported violations, is costly. Regulators face direct costs of levying fines via staff time, negotiation costs, court costs, and appeals expenses. Political economic costs of imposing sanctions arise, as industry groups, political appointees, and politicians may pressure enforcement authorities to treat their constituents more leniently.[6] Regulators certainly behave as if there is a resource cost to sanctions. Civil cases are seldom resolved through trial and usually settled (Glover 2001). If penalties were costless, regulators should increase at least some sanctions to the statutory maximum or to the point where there is no enforcement response. However, sanctions are typically far less than the statutory maximum and an empirical literature shows that enforcement responsiveness is typically positive in regulatory settings (Cohen (1998), Gray and Shimshack (2011), and Leeth (2012). Our conversations with regulators suggest that total legal, administrative, and political costs are substantial and that they increase with the magnitude of penalty. So, we use the simple approximation that expected enforcement costs are proportional to expected penalty. We return to the role of this assumption later.

Regulator's decision problem

We now write out the regulator's decision problem and optimality conditions. To sharpen and simplify the analysis, we consider a case with two types of firm: infrequent and frequent violators. The regulator's choice variable is the expected penalty P_j to impose for a violation by firm type j. This in turn determines the expected violation rate for each type, $V_j\,(P_j)$. As noted above, we treat the cost of imposing the expected fine as proportional to the penalty, with marginal cost of c and a total cost of $c\,P_j$. Of course, fines can only be issued in the event of a violation, so the expected cost of maintaining a credible threat is $c\,P_j\,V_j(P_j)$.

Denote frequent violators by subscripts f and infrequent violators by subscripts i. The Lagrangian representation of the optimization problem with a resource constraint of R is:

$$(1) \qquad \min_{p_i, p_f} V_i(P_i) + V_f(P_f) - \lambda(cP_iV_i + cP_fV_f - R)$$

This yields first order conditions:[7]

[6] Mintz (2014) and Shimshack (2014) discuss the importance of these costs in our subsequent empirical setting.

[7] Note the standard insight about shadow costs holds; we would derive the same first-order conditions in a model where the unconstrained objective function balances compliance and enforcement costs in an additive linear fashion, provided the marginal cost of enforcement resources is constant.

(2) $$FOC_i: \quad \frac{\partial L}{\partial P_i} = \frac{\partial V_i}{\partial P_i} - \lambda\left(cV_i + cP_i\frac{\partial V_i}{\partial P_i}\right) = 0$$

(3) $$FOC_f: \quad \frac{\partial L}{\partial P_f} = \frac{\partial V_f}{\partial P_f} - \lambda\left(cV_f + cP_f\frac{\partial V_f}{\partial P_f}\right) = 0 \ .$$

The first order conditions (2) and (3) have the familiar interpretation that the marginal benefit to the objective function equals the marginal resource cost multiplied by the shadow price of the resource constraint.

Frequent and infrequent violators may differ in $\partial V/\partial P$ and so respond differently to regulator interventions. Differences in $\partial V/\partial P$ are what we term the *enforcement response effect*. It might be intuitively tempting to a regulator to marginally target sanctions to the facility for which this enforcement responsiveness is highest. But, this would ignore the tensions induced by the marginal resource cost.

A key point is that the marginal resource cost will differ systematically between frequent and infrequent violators, which we refer to as the *sanction cost effect*. Costly punishment only occurs conditional on a violation, so it will be relatively expensive to credibly maintain a given level of expected penalty for a violation by a frequent violator because the regulator will be more likely to need to actually impose a penalty. In contrast, it will be relatively inexpensive to maintain the same expected penalty by an infrequent violator because the penalty would need to be imposed less frequently.

To simplify, we rearrange terms and express the first order conditions (2) and (3) in ratio form. This shows the standard result that the ratio of marginal cost to marginal benefit is equal across types at an optimum:

(4) $$\left(V_i + P_i\frac{\partial V_i}{\partial P_i}\right)\bigg/\frac{\partial V_i}{\partial P_i} = \left(V_f + P_f\frac{\partial V_f}{\partial P_f}\right)\bigg/\frac{\partial V_f}{\partial P_f}$$

Note that both c and λ drop out of the ratio form. A further simplification is possible. Rearranging terms yields:

(5) $$P_i + \left(V_i\bigg/\frac{\partial V_i}{\partial P_i}\right) = P_f + \left(V_f\bigg/\frac{\partial V_f}{\partial P_f}\right)$$

Equation (5) is simply a restatement of the requirement in (4) that the ratio of marginal costs to marginal benefits be the same across types. Equation (5) distills the insights of our model into a form that is convenient to operationalize and so serves as the foundation of our subsequent empirical analysis.

The role of stylized assumptions

The optimization framework outlined above uses two main stylized assumptions. Below we discuss the implications of relaxing these assumptions as well as the rationale for using them. The first assumption is costless monitoring. A key point is that the sanction cost effect would still exist even in a model where monitoring is costly. Regardless of how violations are uncovered, sanctioning frequent violators requires higher and thus more costly expected sanctions to maintain a given threat of punishment, exactly because that threat must be frequently backed up for frequent violators. A theoretical and empirical literature suggests that accurate self-reporting can be a reasonable working assumption (i.e. Cohen 1992; Malik 1993, Kaplow & Shavell 1994). We discuss the plausibility of this assumption for our specific empirical application later.

The second assumption is that sanction cost is proportional to expected penalty. This assumption is not critical to our central point in the sense it would be straightforward to adapt a model with the sanction cost effect to some alternative and known relationship between penalty size and sanction cost. However, it also seems a fairly reasonable assumption for our particular setting. To see why this proportionality might naturally arise, consider first a context where only a fraction of violations Q receive a standard sanction S so that that expected penalty $P = Q \times S$. Conditional on choice of S, a standardized cost is incurred for each sanction, so that total costs would be proportional to Q and thus to P. Of course, different sanction magnitudes S may be observed in practice. However, a regulator that seeks to minimize the average total costs of maintaining an expected penalty P would tend to choose sanction S from among the set of sanctions that minimize average cost. A simple implication is that sanction costs must be proportional to P for all sanctions S that are in the cost minimizing set. So, for a regulator that acts to minimize the average costs of maintaining an expected penalty $P = Q \times S$, total costs will be proportional to both Q and S and thus proportional to P.

3. Empirical Setting and Data

We now turn to the relative importance of factors driving the optimal treatment of frequent and infrequent violators in our Clean Water Act (CWA) setting. The CWA requires all water pollution dischargers to hold permits that specify regulated contaminants, pollution limits, and compliance schedules. Effluent limits are technology-based and influenced by sector, sub-sector, and facility size. Realized pollution discharges are stochastic, but a facility can influence average pollution discharges over some period via production controls, abatement equipment and operation, and process modification. Establishment-level compliance can typically be changed rapidly through incremental attention to training, maintenance, and operations. So, changes in compliance do not require large expenditures on new abatement equipment.[8]

Four further issues about CWA oversight bear noting. First, states have primary authority for all permitting, monitoring, and enforcement activities under the CWA. Despite a federally mandated legal structure, states are the regulatory agencies for all practical purposes. Second, like many other regulations, the CWA generally requires agencies to minimize violations, rather than to focus on other objectives like social welfare maximization or minimizing net pollution damages irrespective of permitted obligations. Third, administrative penalties are the workhorse of CWA pollution enforcement. Civil and criminal judicial actions are authorized under the Act, but in practice they are rare for standard water pollution violations.[9] Less formal sanctions like warning letters and notices of noncompliance are common, but the literature suggests that these sanctions 'without teeth' may have little effect on compliance decisions of the large industrial facilities that we study (Shimshack & Ward 2005; Gray & Shimshack 2011). Fourth, CWA authorities have considerable discretion over when and how to issue penalties, but agencies face tightly constrained exogenous budgets. Agencies do not recoup assessed penalties.[10]

Data and sample

Our calibration exercise uses facility-by-month compliance and enforcement data from the USEPA's Permit Compliance System, the Integrated Compliance Information System – National Pollution Discharge Elimination System, and the Enforcement and Compliance History Online databases. We observe pollution violations, inspections, and fines for the universe of CWA "major" industrial wastewater dischargers during our sample period. We focus on major facilities because minor facilities are not necessarily required to report frequently and because states are not

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[8] Primary wastewater treatment involves increasingly fine screening, as well as settling tanks that allow solids to sink to the bottom for removal and oils and foams to rise to the top for skimming. Secondary wastewater treatment involves biological processes where microorganisms breakdown organic matter into less harmful bi-products. These processes are sensitive to small changes in temperature, acidity, light, nutrients, substrate age, and weather, so small changes in attention and maintenance can have large impacts on discharges and compliance. Tertiary treatment, involving chemical or physical-chemical treatment procedures, is less common in our setting.

[9] Civil and criminal actions are typically reserved for situations with extreme harm (i.e. BP oil spill), deliberate lying or records falsification, or unpermitted operations (Uhlmann 2009).

[10] Mintz (2014) and Shimshack (2014) describe these and other institutional pollution oversight institutions in detail.

necessarily required to relay their reports to EPA databases.[11] Supplemental sources of data include county-by-month weather data aggregated from the Global Historical Climatology Network. We obtain state-by-year community characteristics from the Bureau of Labor Statistics, Census Bureau, and Elections Commission.

Our sample covers 1001 industrial CWA major facilities over the period January 2000 to May 2006. We collected compliance data from January 1999 to May 2006 to allow for lags and enforcement data from January 1999 through December 2007 to allow for both lags and leads. Sample start and end dates were chosen for data consistency and reliability reasons.[12] We consider all major CWA industrial enterprises in the 29 US states with 7 or more major facilities with continuous effluent compliance measures during our sample time period.[13] Roughly 46 percent of sample facilities produce chemicals, petrochemicals, and associated products; 19 percent produce wood, paper, and associated products; 17 percent produce metals and associated products; and 18 percent produce other products including food and textiles. Figure 1 summarizes spatial distribution. Facilities are predominantly located in the eastern half of the US, with a majority located in Gulf Coast and Mid-Atlantic states.

Operationalizing compliance and enforcement

Given available data and CWA institutions, we classify noncompliance events as follows. We define a violation as a regulator-designated significant noncompliance (SNC) occurrence for effluent discharges. The advantages of defining violations by SNC are that the measure covers all pollutants simultaneously and provides an externally standardized measure of severity. Because the exact criteria for SNC effluent designations can be complex, it is difficult to fully explain SNC construction here. However, as a general rule, SNCs are triggered when a facility: exceeds permitted allowances for conventional water pollutants (like biochemical oxygen demand and suspended solids) by more than 40 percent multiple times over some monitoring period; exceeds permitted allowances for other water pollutants (like inorganic chemicals and heavy metals) by more than 20 percent multiple times over some monitoring period; exceeds permitted allowances

[11] Industrial majors are those that discharge more than one million gallons of wastewater per day and/or have potential for significant environmental impact.

[12] Historical CWA data in federal EPA data systems becomes available and reliable on a systematic scale around 1998 or 1999, and data migration between EPA systems beginning in June 2006 caused some pollution and compliance information to be inconsistently tracked.

[13] We do not consider municipal wastewater treatment plants. Although these facilities are important causes of point source water pollution, municipal ownership and operation are unlikely to be consistent with the basic economics in our conceptual and econometric frameworks.

for any contaminant by any amount for several monitoring periods in a 6 month window; or exceeds permitted allowances for any contaminant in such a manner as to potentially cause serious water quality or human health issues (USEPA 1996). We do not explore SNC determinations for non-pollution violations arising from paperwork or scheduling issues.

For CWA majors, self-reporting is the dominant form of monitoring.[14] Although self-reporting may not be completely accurate, reasonably accurate self-reporting is plausible in our context for several reasons. Regulators can and do conduct regularly scheduled and ad hoc 'for-cause' on-site inspections. Theory shows that self-reporting systems can be incentive compatible, particularly when penalties for self-reported violations are low and penalties for deliberate falsification are disproportionately high (Malik 1993; Kaplow & Shavell 1994; Innes 1999a, 1999b, 2001). This is the case under the CWA, as most water pollution sanctions are in the thousands (or tens of thousands) of dollars range. In contrast, deliberate records falsification can in incarceration and penalties exceeding hundreds of thousands or even millions of dollars. In many policy contexts, severe sanctioning for misreporting can include personal criminal liability for an employee who falsifies a report thus creating a wedge between the principle and agent (Cohen, 1992). Finally, and notably, a growing literature applies forensic economic tools to CWA industrial facility discharges and fails to reject accurate reporting.[15]

Administrative penalties with monetary fines are the main form of meaningful enforcement for SNC water pollution violations. Although administrative actions may include field citations in some states, the overwhelming majority are issued by administrative law judges. Notably for this work, CWA enforcement guidelines dictate that beyond inducing high levels of compliance, sanction frequency and severity should be influenced by offense history. Other factors may include financial gain, ability to pay, intent, potential damages, and fairness. In practice, a single penalty may cover multiple violations. Many SNC violations are never formally penalized. Conditional on an administrative penalty, fine magnitudes vary substantially across time and space and nearly all penalties are small fractions of amounts allowed under the statute.

Figure 2 summarizes levels and trends in our enforcement and compliance data. Violations are mildly seasonal, with slightly more SNC violations in the winter months. Violations decline

[14] Self-reporting is also the dominant monitoring strategy under several OSHA, FTC, FAA, and FDA programs.
[15] Studies investigating the accuracy of North American industrial water pollution data and failing to reject a null of accurate reporting include LaPlante & Rilstone 1996; USEPA 1999; Shimshack & Ward 2005; Evans et al. 2017.

by roughly 25 percent over the early years of our sample, but remain roughly constant from 2002 to 2006. In total, we observe 2,400 SNC violations between January 2000 and May 2006. In any given month, about 3.1 percent of facilities have a SNC violation. About 33 percent of facilities violate at least once during the full sample period. Administrative fines are also mildly seasonal, peaking in the summer months. Fine numbers decline steadily over the sample period, but fine magnitudes remain constant. In total, we observe 341 administrative fines between January 1999 and May 2006. The median penalty was $5,000, with a mean of $53,000 and an interquartile range of $1,300 to $19,000.

4. Econometric Analysis

The goal of our empirical exercise is to calibrate the first-order optimality condition from Section 2 using data from the CWA setting described in Section 3. We reproduce our first-order condition for convenience:

$$(6) \qquad P_i + \left(V_i \Big/ \frac{\partial V_i}{\partial P_i} \right) = P_f + \left(V_f \Big/ \frac{\partial V_f}{\partial P_f} \right),$$

for types i (infrequent violators) and f (frequent violators). This optimality condition has three basic terms that may differ for across types: expected penalties P, violation rates V, and an enforcement response term defined as the marginal impact of penalties on violations, $\partial V / \partial P$. The average value of the first two of these terms can be reasonably approximated with empirical moments from the dataset. However, approximating the average enforcement response, $\partial V / \partial P$, requires econometrics.

A regression equation explaining facility compliance behavior would ideally relate facility violations V to facility beliefs about penalties conditional on violation, P^b, and other standard explanatory factors.

$$(7) \qquad V = X\mathrm{B} + \gamma P^b + \varepsilon \quad ,$$

where V are violations, X are standard covariates, and P^b are beliefs about punishment conditional on a violation.

There are two core problems when identifying γ in (7), the causal parameter of interest. The first is that beliefs, P^b, are not observed directly. The second is that even if beliefs P^b were observed directly, the error term might be correlated with beliefs. Our approach to both predicaments is to replace the unobservable subjective belief P^b with a proxy prediction $\hat{P}$ based on plausibly exogenous observables.

To motivate our proxy variable approach, suppose first that P^b were observed directly. In that case, a standard two-stage least squares approach would address the endogeneity concern. A first-stage would construct proxy variables $E\left(P^b \mid X, Z\right)$, i.e. expectations of beliefs conditional on some exogenous instrument set Z and other explanatory variables X. Although beliefs P^b are not observable, actually realized penalties P^r are observable. Assuming that facilities do not suffer systematic bias in their enforcement expectations conditional on the instruments, $E\left(P^b \mid X, Z\right) = E\left(P^r \mid X, Z\right)$. Thus, under generally plausible conditions, using a proxy prediction from a first-stage procedure regressing actual penalties for violations P^r on an instrument set Z and exogenous explanatory variables X addresses the problems created by observability and endogeneity.

Of course, since penalties can only be imposed in response to a violation, the first-stage described above can only include the relevant subset of observations corresponding to observed violations. As such, the practical procedure of constructing and using proxy predictions $E\left(P^r \mid X, Z\right)$ in a regression model is a split-sample (two-sample) instrumental variables procedure. See Angrist & Krueger (1992, 1995) and Dee & Evans (2003). Angrist & Pischke (2008) provide a textbook summary.

Implementing the strategy

The mechanics of our split-sample instrumental variables procedure are straight-forward. First, we follow a related literature and identify instruments *Z* based on plausibly exogenous determinants of the state regulators' reputation for toughness at a given time. Second, for facility-months with violations (denoted sample 1), we regress the observed penalties P^r_1 on explanatory variables X_1 and instruments Z_1:

(8) $$P_1^r = X_1\Theta + \delta Z_1 + \mu_1 .$$

We then use estimated coefficients from (8) to form the predicted penalty proxy for the full sample of facility-months (denoted sample 2):

(9) $$\hat{P}_2 = X_2\hat{\Theta} + \hat{\delta} Z_2 .$$

Finally, in the spirit of two-stage least squares, the penalty proxy becomes the explanatory variable of interest in the behavioral equation:

(10) $$V_2 = X_2 \mathrm{B} + \gamma \hat{P}_2 + \varepsilon_2 .$$

This two-stage approach provides consistent parameter estimates. The only substantive difference between the approach outlined above and the standard two-stage least squares inferential procedure is the sample for the first stage.

Of course, practical implementation of this approach requires an instrument Z. To be valid, Z must be correlated with a regulator's propensity to sanction in a given period (i.e. their reputation for toughness with the facility). Regulator propensity to sanction differs markedly over space and time, and differences are driven by shocks to local political, economic, and budgetary conditions (Shimshack 2014). A natural source of information on a regulator's propensity to sanction at a given time is that agency's visible recent history of strictness (Sah 1991). Thus, a related deterrence literature uses penalties levied on other firms in the same jurisdiction (i.e. state) in the recent past as an indicator of regulator reputation for strictness (Shimshack & Ward 2005, 2008). We use the same variable as an instrument in the construction of our proxy $\hat{P}_2$ from the first-stage of our two-stage least squares procedure.

We construct Z to plausibly satisfy the standard exclusion restriction that Z must not directly influence facility behavior in the period of interest, at least in a conditional sense. First, we omit penalties on the facility itself to avoid reverse causality induced by regulator targeting. Second, we lag penalties on others to avoid contemporaneous correlation at the state level. Third, we condition on year indicators to avoid spurious correlation caused by common time trends. Nevertheless, we do need to assume that lagged penalties on others in the same jurisdiction are then conditionally uncorrelated with the error term. Although it remains possible that a serially-correlated state-specific omitted shock could induce such a correlation and so violate the exclusion restriction, we consider the evidence for this possibility in the robustness section and find the concern unlikely to drive results.

Implementation of our exercise also requires operationalizing compliance types empirically. Our main analysis divides the sample of facilities into two fixed groups corresponding to the total number of violations over the full compliance sample. In this case, we run the main regression separately for each group, i.e. we estimate the marginal impact of penalties on compliance separately for frequent violators and infrequent violators. The initial assumption of time invariant and exogenous compliance types seems reasonable, as the large industrial facilities in our sample have typically been regulated under similar CWA conditions for decades and this long history of interaction would suggest that type had been largely revealed. That is, it seems unlikely that the regulator is learning much new about facility type over our particular sample period. Nevertheless, we acknowledge that group transitions may occur in some instances, like after management changes or installation of new equipment, so we later explore sensitivity to allowing transitions between types based on time-varying recent compliance history in the robustness section.

We note several specification details. To fix ideas in presentation, equations (7) – (10) illustrated the simplest fully linear cases. However, in our econometrics we pragmatically follow the related literature by defining all penalty variables using a logarithmic transformation of fines plus one. The log transformation makes the penalty data less skew and adding one sets the transformed value to zero when there is no fine. In first-stage regressions, the dependent variable is log fines attributed to the given violation plus one.[16] In first-stage regressions, the key explanatory variable is the regulator reputation effect proxy constructed by summing logged fines plus one in the past year over all other facilities in the same state. In second-stage regressions, the key dependent variable is a violation by facility j in period t. Since this is a limited dependent variable, we estimate both linear probability and probit models. The key explanatory variable is the predicted penalty proxy for facility j in period t.

Other specification details are as follows. In all regressions, covariates X consist of standard explanatory factors including rainfall, year dummies, seasonality dummies, and industry (SIC) dummies. Some specifications include state or facility fixed effects. Further specifications include time-varying local community characteristics such as unemployment, income, and Republican vote share. In all regressions, frequent violators are initially defined as those with four or more violations (months of violation) during the January 1999 to May 2006 compliance period. Infrequent violators are facilities not defined as frequent violators. As noted, we later explore robustness to alternate type definitions. All presented standard errors are clustered at the state-level unless otherwise noted.

[16] We assign fines to specific effluent violations by apportioning each fine to those violations at the facility in the preceding twenty-four months. Although penalties in our dataset are not directly linked with violations, we were able to identify legal records for some of the fines and those fines were indeed for the SNC violations we assigned them to. For our attribution procedure, if a single fine covered multiple violations or multiple fines were preceding by a single violation, we proportionately assigned fine magnitudes to violations. Results are generally robust to assigning fines based on SNC violations in the past 12 months rather than 24 months.

Econometric results

First, we show that frequent violators are punished more severely than infrequent violators. Figure 3 summarizes average fines per violation across types in the raw data and considers robustness of the result across different types. The graphs in the center column use baseline definitions for frequent and infrequent violators. The key lesson from Figure 3 is that frequent violators are penalized significantly more harshly than infrequent violators for similar infractions. The top panel illustrates that fines per violation are roughly six times higher for frequent violators than for infrequent violators. Since many violations are not penalized, the top panel includes $0 penalties. The bottom panel therefore replicates the comparisons excluding $0 penalties, i.e. conditional on a fine being levied. Conditional fines per violation are still roughly three times higher for frequent than for infrequent violators.

Table 1 presents main enforcement response econometric results. Table 1 columns [1] and [2] present estimates from our first-stage regressions. Key results are in the first row. Lagged fines on others in the same state, the sources of identifying variation, are economically and statistically significant predictors of future fines conditional on violations. So, facilities can learn about their regulator's propensity to sanction by observing the regulator's recent behavior. The other coefficient of direct interest is in the third row. Interpreting coefficient magnitude on the frequent violator dummy variable of roughly 1.1, observed penalties conditional on a violation for frequent violators are roughly twice as large as observed penalties conditional on a violation for infrequent violators.[17] The magnitude of the frequent / infrequent violator penalty difference relative to the comparable difference in the raw data (i.e. in Figure 3) is due to the inclusion of covariates. Table 1 columns [1] and [2] also include estimates for controls that are included because they belong in the second-stage equation. First-stage F-statistics for columns [1] and [2] are roughly 12 and 88.

Table 1 columns [3] through [10] present estimates from our second-stage violation / compliance equations of interest. The key results are in the second row. Looking at columns [3] through [6], we find that the penalty proxy is an economically and statistically significant predictor of violations for infrequent violators. Looking at columns [7] through [10], we find that penalty proxy is also an economically and statistically significant predictor of violations for frequent violators. Comparing coefficient magnitudes across types shows that frequent violators are absolutely more sensitive to marginal changes in expected penalty. However, when scaled by

[17] In log-level specifications, the percent impact of a dummy switch from 0 to 1 is 100[exp(coefficient) - 1].

average propensity to violate, infrequent violators are more sensitive to marginal changes in expected penalty. Interpreting coefficient magnitudes given baseline violation rates, we find a relative deterrence elasticity for infrequent violators of around .15 to .20 and a relative deterrence elasticity for frequent violators of around .08 to .10.[18]

We next discuss effects of control variables in our second-stage violation equations. We find that rainfall is a significant predictor of violations for infrequent but not for frequent violators. This is consistent with accidental or stochastic factors importantly influencing average compliance outcomes for infrequent violators but not for frequent violators. We find few reliably significant relationships between our community characteristic controls and violations. This may be consistent with community characteristics influencing compliance indirectly through regulatory channels but not directly through other channels.[19] As in the raw data, violations trend downward over time, are seasonal with peaks in winter months, and are more common among chemical and associated product producers.

Sensitivity and Robustness

Omitted variables. Our empirical exploration presumes that lagged enforcement actions directed towards others, i.e. the agency 'reputation' proxy, is exogenous in the second-stage regression and thus satisfies an exclusion restriction. Although we construct this variable omitting the facility itself and with lags to mitigate endogeneity concerns, it remains possible that specific types of omitted variables could bias results. One natural concern is that enforcement intensity and violations may be correlated through time-varying national shocks. However, our analysis includes year indicators. Another worry is the lagged proxy is correlated with the error term in the second stage violation equation via a state-specific omitted variable influencing both overall enforcement intensity and compliance in the state. However, we replicated the analysis with state-level fixed effects and found similar results. Appendix Table 1 presents results. Columns [1] to [2] and columns [4] to [5] are generally similar. A specification test fails to reject the null of no difference in coefficients across specifications with and without state-level fixed effects.[20]

[18] In level-log specifications, the point elasticity is the coefficient divided by the baseline for the dependent variable.

[19] Other papers using CWA data find similar results (Shimshack and Ward 2005, 2008). We do find statistically significant relationships between vote share and violations for infrequent violators and between unemployment and violations for frequent violators. It is possible that vote share and unemployment is correlated with production for these facilities, although time varying production data are not available at the facility level. We note that inclusion or omission of community characteristics has little impact for key enforcement sensitivity estimates.

[20] For reference, Appendix Table 1 also presents results from regressions with facility fixed effects. Much of the identifying variation has been swept out of the model. Note, however, that using the (smaller) fixed effects estimates

A more subtle threat to identification is a time-varying, state-specific political or economic shock. To fix ideas, consider a statewide positive economic shock. Such a shock might, for example, induce facilities to violate more often due to enhanced profit opportunities while also injecting resources into the state environmental budget and increasing overall enforcement intensity. We believe such shocks are unlikely to drive our results for several reasons. First, the shock must be persistent to bias the results, since our measures are lagged. Second, some of our specifications include time-varying state-level covariates like unemployment, per capita income, and Republican vote share. These measures are intended to pick up the most obvious of time-varying omitted variables, yet including or omitting them has almost no effect on coefficients for the 'regulator reputation' variable. Coefficients on the penalty proxy in Table 1 columns [3] vs. [4], [5] vs. [6], [7] vs. [8], and [9] vs. [10] are statistically indistinguishable and within 4 percent of each other. Had time varying statewide shocks been importantly driving results, we would have expected to find meaningful differences in estimates between specifications omitting or including the most obvious of statewide economic or political variables (i.e. unemployment, income, vote shares). Of course, our three measures don't capture all possible omitted variables, but the evidence available to us is at least consistent with small bias due to time-varying omitted variables.

Frequent and infrequent violator definition. Our analysis divides the sample into frequent and infrequent violator types defined by the number of violations over the entire sample period. Our specific cut-off is 4 violations, which splits facilities into groups of roughly 20 percent frequent and 80 percent infrequent violators. To explore robustness, we replicated the analysis with cut-offs at 3 and 5 violations. Appendix Table 2 presents results. Penalty proxy coefficients for infrequent violators in columns [1] and [3] are statistically similar and within 18 to 31 percent of the main estimates in column [2]. Penalty proxy coefficients for frequent violators in columns [5] and [7] are statistically similar and within 17 to 37 percent of the main estimates in column [6].

Our main analysis is implemented as if type is fixed and known to the regulator ex-ante. The idea is that average propensity to violate may be largely a function of facility characteristics that change slowly over time, and a long history of regulatory interactions preceding our sample period revealed type for most facilities. To confirm that the fixed type assumption is not driving our results, we replicated our analysis allowing type transitions during the sample period. We

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for frequent violators in our final calibration exercise (next section) simply increases the magnitude of the final empirical result and does not impact the exercise's qualitative message nor its statistical significance.

defined frequent violators as those facilities with a violation in the past year and infrequent violators as those facilities without a violation in the past year. Appendix Table 2 demonstrates that results are reasonably robust to allowing type transitions. Penalty coefficients for types defined by recent compliance history in columns [4] and [8] remain statistically significant at conventional levels and fall within 1 percent (infrequent violators) and 57 percent (frequent violators) of main estimates in columns [2] and [6].[21] We do not find strong evidence that allowing transitions meaningfully changes our punchlines.

Standard errors. To confirm robustness of inference, we replicated our analysis using a bootstrap procedure, preserving the panel structure of the data, in the spirit of Bjorklund and Jantti (1997). The standard error on the key penalty proxy coefficient for infrequent violators in Table 1, column [3] changes from .00014 to .00018. The standard error on the key penalty proxy coefficient for frequent violators in Table 1, column [7] changes from .0050 to .0057. The bootstrap approach does not generate meaningful change in inference.

Violation magnitude. A final concern with our analysis is that frequent and infrequent violators may experience violations of different severity. Recall that we use a predefined CWA dichotomous definition of significant noncompliance (SNC). To explore the plausibility that our analysis "compares apples to apples," we matched a subsample of our facilities to a supplemental dataset containing information on numerical discharges and discharge limits for the common conventional water pollutants total suspended solids (TSS) and biochemical oxygen demand (BOD). The average TSS violation (conditional on TSS violation) was 210 percent of the permitted standard for frequent violators and 215 percent of the permitted standard for infrequent violators [N = 831 facilities]. The average BOD violation (conditional on BOD violation) was 178 percent of the permitted standard for frequent violators and 173 percent of the permitted standard for infrequent violators [N = 575 facilities]. Observed violations, conditional on significant noncompliance, are similar in severity across compliance types.

5. Findings and discussion

We are now in a position to answer our motivating question using CWA data: Should a regulator attempting to minimize violations subject to a fixed budget constraint and costly sanctions reallocate the marginal enforcement dollar towards violations committed by frequent

[21] Note that using the (larger) frequent violator enforcement sensitivity estimate in the next section's final calibration exercise mildly reduces the magnitude of the final result but does not affect the qualitative message or significance.

violators or towards violations committed by infrequent violators? To answer the question, we plug our estimates into an empirical analogue of equation (6).

As previously noted, the average value of expected penalties P and violation rates V for frequent violators (type f) and infrequent violators (type i) can be approximated from moments of our sample data. The marginal impact of penalties on violations, the enforcement response effect, $\partial V / \partial P$ for each type was the subject of our econometric estimation. The only additional issue is that our empirical analogue of (6) requires a transformation given the level-log specification. Note if $V = X\mathrm{B} + \gamma \log P$, then $\partial V / \partial P = \gamma / P$. Thus, equation (6) can be rewritten as:

(7) $$P_f\left(1 + V_f / \gamma_f\right) = P_i\left(1 + V_i / \gamma_i\right).$$

The condition in (7) still has the natural interpretation of a standard first-order condition. The ratio of marginal costs to marginal benefits must be the same across types for the regulator to optimally allocate enforcement resources. If the two sides are not equal, the regulator is inefficiently allocating enforcement resources if its goal is to maximize compliance. If the absolute value of the left-hand side of (7) is larger than the absolute value of the right-hand side, then the ratio of marginal costs to marginal benefits from deterring violations by frequent violators is higher in practice than the ratio of marginal costs to marginal benefits from deterring violations by infrequent violators.

Plugging in the empirical parameters necessary to calibrate (7) yields:

(8) $$\left|3076\left(1 - .1307/.0115\right)\right| \quad > \quad \left|498\left(1 - .0041/-.00059\right)\right|.$$ [22]

The left-hand side of (8) is more than ten times larger than the right-hand side. This means that the ratio of marginal costs to marginal benefits from deterring CWA violations by frequent violators is more than ten times greater than the ratio of marginal costs to marginal benefits from deterring CWA violations by infrequent violators. To explore robustness, we bootstrapped the test statistic using 5000 replications. The ratio of marginal costs to marginal benefits remained higher for frequent violator infractions than for infrequent violator infractions in more than 99.3 percent of

[22] 3076 and 498 represent the mean (expected) penalties per observed violation, by frequent and infrequent violator types. Recall that these values of P are low relative to overall average penalties in the dataset because many violations are not fined and because many fines address multiple violations. 0.1307 and 0.0041 represent the number of significant violations per facility per month, by frequent and infrequent violator types. -0.0115 and -0.00059 are the econometrically estimated enforcement sensitivity parameters obtained in Section 4.

replications. We reject a null hypothesis that CWA regulators are optimally deterring violations across types.

Discussion

This paper's point of departure is that sanctions are costly to regulators. Direct investigation, negotiation, and court costs are substantial. Indirect political economic costs and pressures are also important. Our primary conceptual contribution is to show that a regulator motivated to achieve high compliance given costly sanctions and limited resources must consider two effects when optimizing the treatment of violations committed by frequent vs. infrequent violators: an enforcement response effect and a sanction cost effect. Casual intuition – and the preceding literature – largely overlooks the second mechanism: it is relatively cheap to maintain a given expected threat against infrequent violators because the regulator need not back up threats with costly sanctions very often for this group. Violations by infrequent violators may simply be inexpensive to prevent. Although it may seem remarkable that we analyze the importance of sanction costs without direct measures of regulator expenditures or resource constraints, this is ultimately no more surprising than the standard Lagrange multiplier canceling out of the ratio of first-order conditions in textbook optimizations.

Our main empirical contribution is a stark illustration that harsher treatment of violations by frequent violators – as is standard practice at regulatory agencies around the world – can be counterproductive if the goal is to maximize compliance. In our industrial Clean Water Act setting, we find that the ratio of marginal costs to marginal benefits (the 'buck per bang') is more than ten times higher for enforcement resources directed towards violations by frequent violators. This is due to a sanction cost effect, not because infrequent violators are marginally more responsive to the threat of punishment. More generally, we believe that our empirical apparatus can be used in other regulatory settings by agencies considering the optimal treatment of frequent and infrequent violators. In any setting where compliance is reasonably observed through self-reporting, continuous monitoring, etc., regulators have ready access to average penalties and violation rates, and deterrence effects can be estimated by in-house statisticians or outside researchers.

We note two main limitations. First, to keep our work focused, this paper considers a case where the costs of observing violations are low, as in regulatory settings with self-reporting or continuous monitoring. We do not consider the costs of inspection and detection in the analysis. These costs are important in many settings, but a key point is that our main mechanism remains applicable. Previous research that accounts for costly monitoring but not costly enforcement overlooks a crucial feature of economically optimal regulatory behavior. Second, we have limited direct information on enforcement costs. We are unable to identify the specific global optimum, but as noted above, we are able to identify the direction of an optimum relative to existing practice. More complete information on administrative, legal, and political costs of regulatory punishment is an important area for future research.

The above issues notwithstanding, notable policy implications arise from our work. CWA agencies currently punish violations by frequent violators far more severely than violations by infrequent violators; on the margin, this behavior actually lowers total compliance. Common proposals to compensate for declining overall pollution enforcement budgets with an even greater emphasis on frequent violators may make matters worse.[23] Our methods may apply to similar policy questions in other regulatory settings. Consider, as one illustrative example, that the Department of Commerce's Office of the Inspector General proposed that NOAA fisheries should entirely eliminate sanctions for first-time and infrequent violators (USDOC 2010).

This research is intended to be positive rather than normative. Regulators may have objectives beyond maximizing total compliance, including potentially important fairness and ethical considerations. Our results are predicated on existing institutions, practices, and the observed range of variation in the data. We are nowhere suggesting equal or higher penalties for violations by infrequent violators. Instead, this research simply serves to highlight that especially lenient treatment of infrequent violators relative to especially harsh treatment of frequent violators involves efficiency trade-offs and may not achieve desired outcomes. Regulators are acutely aware that sanctions are costly, but the full implications of those costs for the relative treatment of frequent and infrequent violators have not yet have entered the regulatory or scholarly dialogue.

[23] A draft EPA strategic plans referenced "fiscal constraints" on several occasions and called for as much as a 40 to 50 percent reduction in enforcement activities. Proposals around the same time recommended maintaining regulatory threats by focusing greater attention towards frequent violators (USEPA 2008, 2013).

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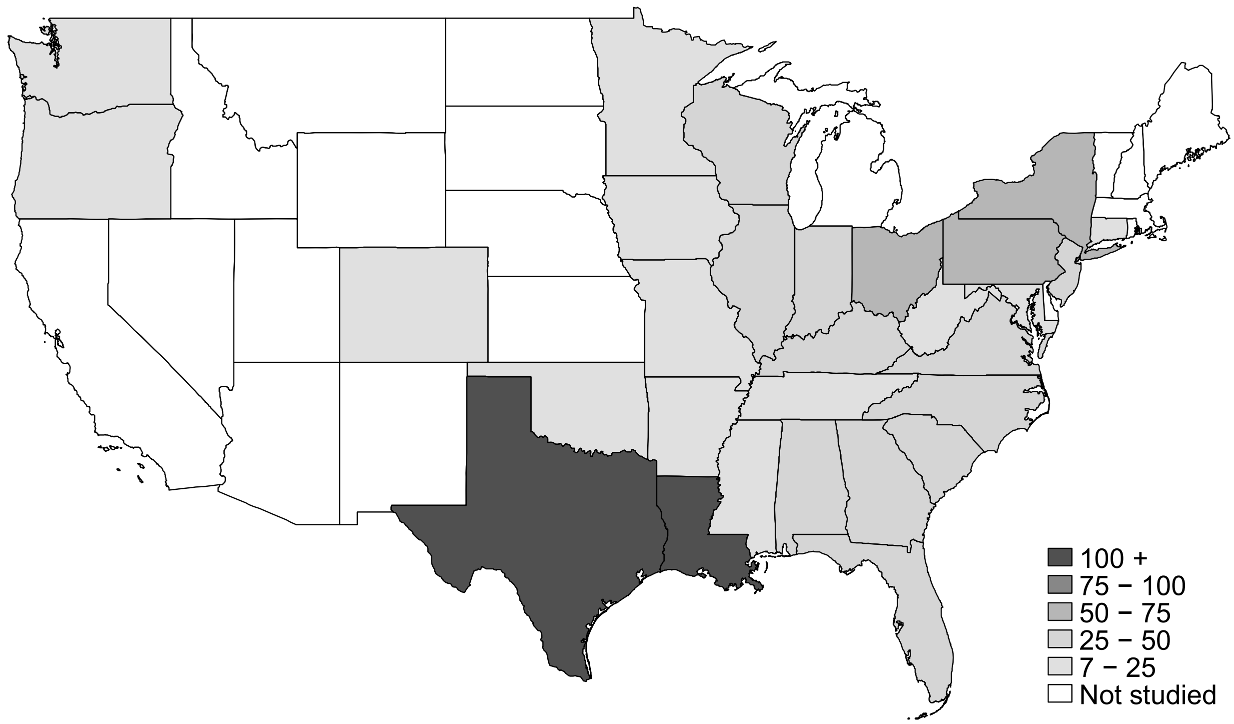

Figure 1. Number of sample facilities per state. Our 1001 sample CWA establishments are located in the eastern half of the United States and the industry-intensive states of TX, CO, WA, and OR. For inclusion, sample states must have 7 or more CWA major industrial facilities and compliance/enforcement data spanning 1999 to 2006.

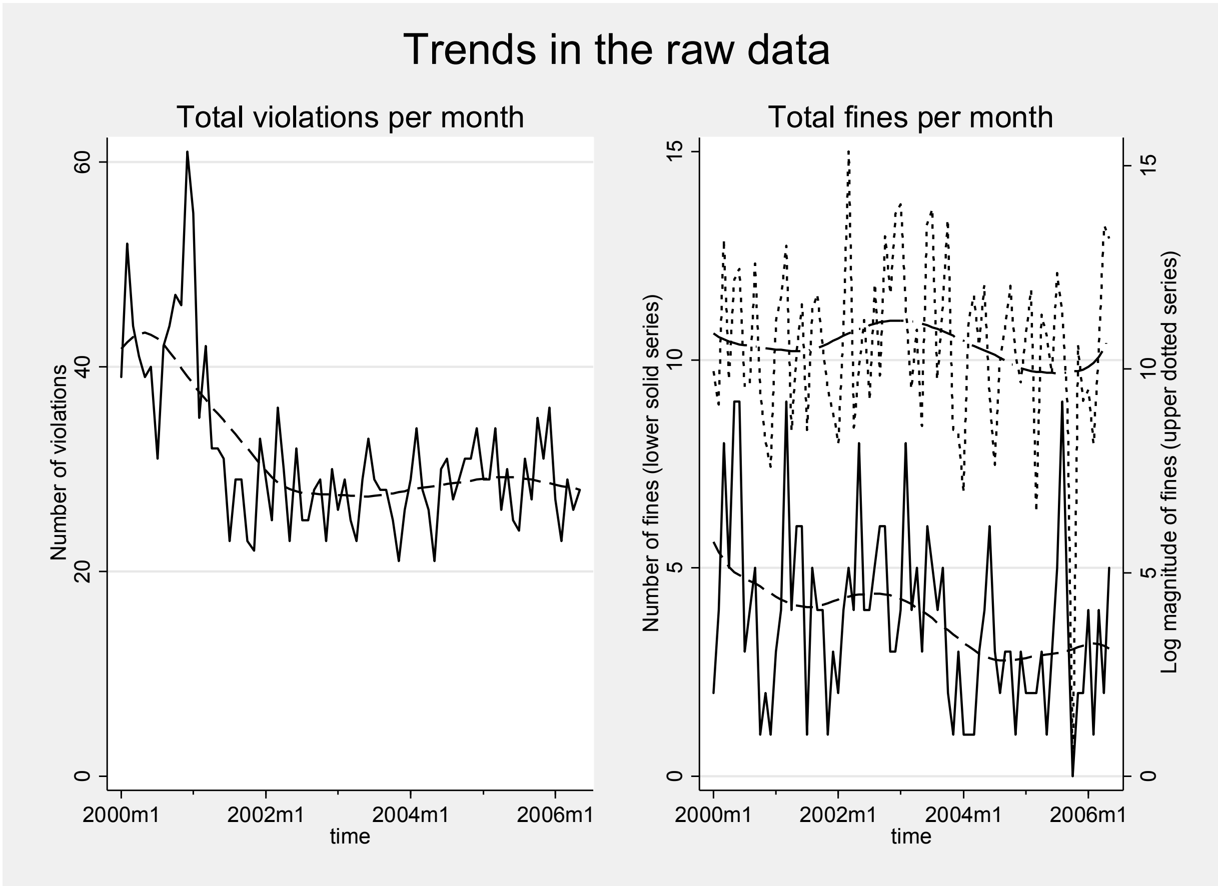

Figure 2. Trends in the raw violations and fines data. Violations, number of fines, and log-scale fine magnitudes display seasonality and generally trend downward. All three series also display considerable idiosyncratic variation. The uptick in violations during early 2001 is not apparent in regression year dummies, suggesting these data points will be explained by features of our model.

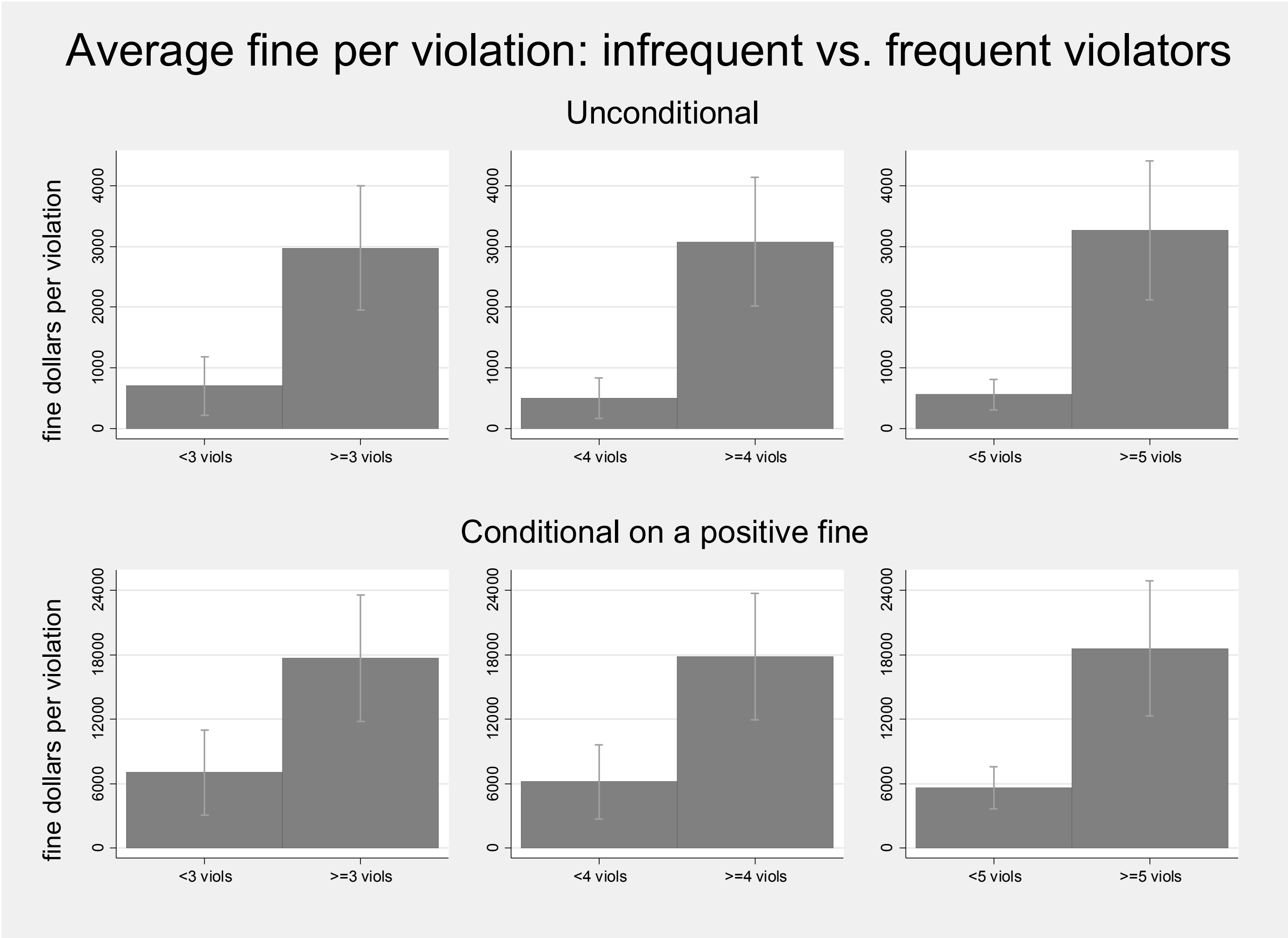

Figure 3. Average fines per violation across infrequent and frequent violators. The top row compares average fine per violation across types. Many violations by both types are not fined, so the bottom row presents the same comparison conditional on a positive fine. In each row, the three graphs represent different definitions of ‘infrequent’ vs. ’frequent’ violators. Two key points emerge. First, frequent violators are punished far more severely for equivalent violations. Second, modestly different definitions of frequent violator have little impact on the overall patterns observed.

TABLE 1. Main econometric estimates

	FIRST STAGE: PENALTY PREDICTION EQ.		SECOND STAGE: INFREQUENT VIOLATORS				SECOND STAGE: FREQUENT VIOLATORS			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
Dependent Var.	Fines	Fines	Violation	Violation	Violation	Violation	Violation	Violation	Violation	Violation
Sample Restriction	Months w/ Violations	Months w/ Violations	All Months	All Months	All Months	All Months	All Months	All Months	All Months	All Months
Specification	OLS	OLS	Linear Probability	Linear Probability	Probit	Probit	Linear Probability	Linear Probability	Probit	Probit
Fines per plant on others 1-12 months ago	2.657** (0.417)	2.634** (0.379)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Penalty Proxy	n/a	n/a	-0.00059** (0.00014)	-0.00057** (0.00014)	-0.00076** (0.0002)	-0.00073** (0.00018)	-0.0115** (0.0050)	-0.0112** (0.0046)	-0.0136** (0.0068)	-0.0133** (0.0063)
Frequent Violator	1.041** (0.417)	1.122** (0.422)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Rainfall	0.333 (0.332)	0.353 (0.297)	0.0020** (0.0008)	0.0023** (0.0008)	0.0018** (0.0005)	0.0020** (0.0005)	0.00037 (0.0153)	0.0052 (0.0151)	0.0055 (0.0164)	0.0070 (0.0163)
Unemployment	-	-0.550** (0.266)	-	-0.0006 (0.0004)	-	-0.0007 (0.0004)	-	-0.0248** (0.0113)	-	-0.0257** (0.0113)
Income	-	-0.151** (0.037)	-	-0.0001 (0.0001)	-	-0.0001 (0.0001)	-	-0.0002 (0.0002)	-	-0.0003 (0.0001)
% Vote Repub	-	-7.475 (4.701)	-	-0.0134** (0.0051)	-	-0.0140** (0.0045)	-	-0.1853 (0.1455)	-	-0.2001 (0.1520)
Year Fes	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Season FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,410	2,410	60,522	60,522	60,522	60,522	16,555	16,555	16,555	16,555
# Facilities	328	328	786	786	786	786	215	215	215	215
BaselineViol	n/a	n/a	0.0041	0.0041	0.0041	0.0041	0.1307	0.1307	0.1307	0.1307

NOTES: Clustered standard errors in parentheses. *, ** indicate significant at 10, 5 percent levels. Probit estimates are marginal effects.

APPENDIX TABLE 1. Robustness to Fixed Effect Specifications

	INFREQUENT VIOLATORS			FREQUENT VIOLATORS		
	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Var.	Violation	Violation	Violation	Violation	Violation	Violation
Fixed Effects	No state or facility FEs	State Fes	Facility FEs	No state or facility FEs	State FEs	Facility FEs
Penalty Proxy	-0.00059**	-0.00071**	-0.00067**	-0.0115**	-0.0065**	-0.0050
	(0.00014)	(0.00015)	(0.00015)	(0.0050)	(0.0041)	(0.0046)
Rainfall	0.0020*	0.0023**	0.0020**	0.00037	0.00088	0.0379**
	(0.0008)	(0.0007)	(0.0006)	(0.0153)	(0.0158)	(0.0115)
Year FEs	YES	YES	YES	YES	YES	YES
Season FEs	YES	YES	YES	YES	YES	YES
Industry FEs	YES	YES	YES	YES	YES	YES
State FEs	NO	YES	NESTED	NO	YES	NESTED
Facility FEs	NO	NO	YES	NO	NO	YES
Observations	60,522	60,522	60,522	16,555	16,555	16,555
# Facilities	786	786	786	215	215	215
BaselineViol	0.00408	0.00408	0.00408	0.1307	0.1307	0.1307

NOTES: Standard errors in specifications [1], [3], [4], and [6] clustered at the facility level. Standard errors in specifications [2] and [5] clustered at the state level. *, ** indicate significant at 10, 5 percent levels.

APPENDIX TABLE 2. Robustness to definitions of frequent and infrequent violators.

	INFREQUENT VIOLATORS				FREQUENT VIOLATORS			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Dependent Var.	Violation	Violation	Violation	Violation	Violation	Violation	Violation	Violation
Frequent Violator Definition	3 or more violations	4 or more violations	5 or more violations	Violation in the past 12 months	3 or more violations	4 or more violations	5 or more violations	Violation in the past 12 months
Penalty Proxy	-0.00041**	-0.00059**	-0.00048**	-0.00058**	-0.0095*	-0.0115**	-0.0158**	-0.0180*
	(0.00015)	(0.00014)	(0.00018)	(0.00011)	(0.0047)	(0.0050)	(0.0061)	(0.0103)
Rainfall	0.0019**	0.0020*	0.0036**	0.0032**	0.00017	0.00037	0.00046	-0.0031
	(0.0008)	(0.0008)	(0.0012)	(0.0014)	(0.0128)	(0.0153)	(0.0204)	(0.0279)
Year Fes	YES	YES	YES	YES	YES	YES	YES	YES
Season Fes	YES	YES	YES	YES	YES	YES	YES	YES
Industry Fes	YES	YES	YES	YES	YES	YES	YES	YES
Observations	58,135	60,522	64,141	68,744	18,942	16,555	12,936	8,333
# Facilities	755	786	833	n/a[a]	246	215	168	n/a[a]
BaselineViol	0.00292	0.00408	0.00635	0.00532	0.1183	0.1307	0.1548	0.2453

NOTES: Clustered standard errors in parentheses. *, ** indicate significant at 10, 5 percent levels. [a] Infrequent violators and frequent violator facility numbers are not constant for the violator classification that allows switching.

APPENDIX A. Selected U.S. Regulatory Agency Enforcement Guidelines

U.S. Department of Commerce (USDOC). 2010. Office of the Inspector General. Final Report: Review of NOAA Fisheries Enforcement Programs and Operations. Report No. OIG-19887-2.

U.S. Department of Labor. 2013. Occupational Safety and Health Administration. Severe Violator Enforcement Program: White Paper.

U.S. Environmental Protection Agency (USEPA). 1989. Office of Water. The Enforcement Management System: National Pollutant Discharge Elimination System.

U.S. Environmental Protection Agency (USEPA). 1998. Office of Enforcement and Compliance Assurance. Issuance of Policy on Timely and Appropriate Enforcement Response to High Priority Violations. EC-P-1999-03.

U.S. Federal Energy Regulatory Commission (USFERC). 2008. Revised Policy Statement on Enforcement. Docket No. PL08-3-000.

U.S. Health and Human Services (USHHS). 2011. Food and Drug Administration. Regulatory Procedures Manual.

U.S. Securities and Exchange Commission (USSEC). 2013. Division of Enforcement. Office of Chief Counsel. Enforcement Manual. October 9, 2013.